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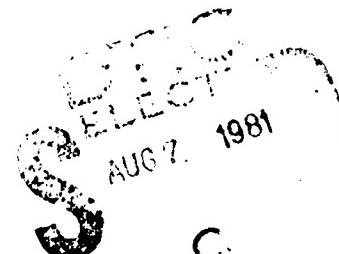
SOLVING MULTIACTIVITY MULTIFACILITY
CAPACITY-CONSTRAINED 0-1 ASSIGNMENT PROBLEMS

by

Krishan Lal Chhabra

Serial T-441
12 May 1981

The George Washington University
School of Engineering and Applied Science
Institute for Management Science and Engineering



Program in Logistics
Contract N00014-80-C-0169
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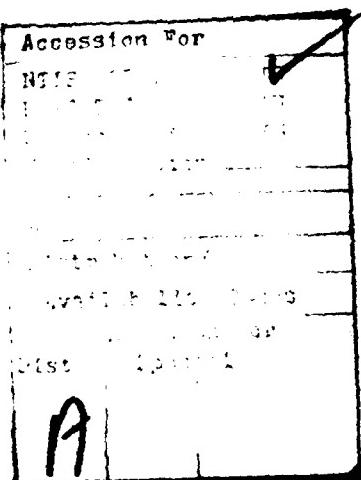
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A branch-and-bound solution algorithm and a computer program implementing this algorithm are developed to solve multiactivity multifacility capacity-constrained 0-1 assignment problems. Such 0-1 integer programming problems have the objective of minimizing the sum of variable costs due to the assignment of the activities to designs and fixed costs due to the inclusion of the facilities chosen. The constraints ensure that each activity is assigned to a single design and that the capacities of the facilities chosen are not exceeded. Each design involves the use of one or more facilities, and the same design may be used by several activities. This document includes formulation of the problem, mathematical development of the branch-and-bound solution algorithm, a detailed test example, and computational test results using the computer program. The areas of application are identified, and consideration for further improvement of the branch-and-bound solution algorithm are also included.

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SOLVING A MULTIACTIVITY MULTIFACILITY
CAPACITY-CONSTRAINED 0-1 ASSIGNMENT PROBLEM

by

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A Dissertation submitted to

The Faculty of

The School of Engineering and Applied Science
of The George Washington University in partial satisfaction
of the requirements for the degree of Doctor of Science

May 3, 1981

Dissertation directed by

Richard Martin Soland

Professor of Operations Research

Abstract

SOLVING A MULTIACTIVITY MULTIFACILITY CAPACITY-CONSTRAINED 0-1 ASSIGNMENT PROBLEM

by

Krishan Lal Chhabra

Richard Martin Soland, Director of Research

A branch-and-bound solution algorithm and a computer program implementing this algorithm are developed to solve a multiactivity multifacility capacity constrained 0-1 assignment problem. The mathematical formulation for such a problem, called problem (P), is to find x_{ij} and y_k values that:

$$\text{Minimize } \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k y_k \quad (i)$$

$$\text{subject to } \sum_{i=1}^m x_{ij} = 1 \quad j=1, \dots, n \quad (ii)$$

$$\sum_{i=1}^m \sum_{j=1}^n d_{ijk} x_{ij} \leq s_k y_k \quad k=1, \dots, p \quad (iii)$$

$$x_{ij} = 0 \text{ or } 1 \text{ for all } i \text{ and } j \quad (iv)$$

$$y_k = 0 \text{ or } 1 \text{ for all } k \quad (v)$$

where i , j , k are indices for designs, activities, and facilities, respectively; x_{ij} has value 1 if and only if activity j uses design i , and y_k has value 1 if and only if facility k is used. A design involves the use of one or more facilities, and the same design may be used by several activities.

Problem (P) has the objective of minimizing the sum of a_{ij} 's -- the variable costs due to the assignments of activities to designs, and b_k 's -- the fixed costs due to the facilities used. Constraints (ii) and (iv) ensure that each activity is assigned to a single design. Each d_{ijk} is the capacity required at facility k if activity j uses design i , and is thus equal to zero if design i does not involve the use of facility k . Constraints (iii), therefore, ensure that for each facility k used, the total capacity required does not exceed the capacity available s_k . The difficulty in solving problem (P) stems from the indirect relationship between the assignments and facilities, i.e., an assignment $x_{ij} = 1$ bears on all the constraints (iii) for which d_{ijk} is positive, and, therefore, on several y_k variables.

The branch-and-bound solution algorithm uses Lagrangian relaxation as a basic step in obtaining lower bounds. In addition, it includes several operational rules, such as a branching rule for a judicious choice of the branching variable, a capacity rule to eliminate infeasible assignments, and a bounding rule to eliminate non-optimal assignments.

This dissertation includes relevant background leading to the formulation of problem (P), mathematical development of the branch-and-bound solution algorithm, a detailed test example, and computational test results using the computer program. The areas of application are identified, and suggestions for further improvement of the branch-and-bound solution algorithm are included.

The computer program has been written in FORTRAN IV. A detailed description of the computer program and guidelines for its use are included in a separate document entitled "Program Description and User's Guide for ZIPCAP--a Zero-one Integer Program to solve multiactivity multifacility Capacity-constrained Assignment Problems." Although developed for capacitated problems, the computer program can also be used to solve uncapacitated problems in which it is assumed that the facilities have infinite capacity.

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1. INTRODUCTION

Multiactivity multifacility assignment problems arise in such diverse areas as public health care systems and private multi-echelon inventory/distribution systems. Such systems involve the assignment of activities or tasks to groups of facilities in such a way that total system cost is minimized. The total system cost has components (fixed costs) that depend on the facilities actually used as well as components (variable costs) that depend solely on the assignment made. Most recently [Gross, Pinkus, and Soland (1979)] there has been interest in including facility capacity constraints as well. For this kind of problem, i.e., a multiactivity multifacility capacity-constrained 0-1 assignment problem, we have developed a solution algorithm of the branch-and-bound type and a computer program based upon it.

The computer program and guidelines for its use are described in a separate document [Chhabra and Soland (1980)] titled "Program Description and User's Guide for ZIPCAP -- a Zero-one Integer Program to solve multiactivity multifacility Capacity-constrained Assignment Problems."

This document describes the development of the solution algorithm and computational test results using the computer program. Suggestions for further improvement in the solution algorithm are also included.

This chapter reviews the relevant literature, provides background leading to the mathematical formulation of the multiactivity multifacility capacity-constrained 0-1 assignment problem, called problem (P), and includes potential areas of application. The theoretical base for developing the algorithm/methodology are described in Chapter 2. Various components of the methodology are covered in detail in Chapter 3. Chapter 4 provides an overview of the computational procedure and the computer program, whereas computational test results are given in Chapter 5. Suggestions for further research and potential improvements in the algorithm are included in Chapter 6.

It may be noted that the basic terminology, described below, in the formulation of problem (P) includes: activities that must be assigned, facilities which serve the activities, designs involving one or more facilities, fixed costs associated with the facilities, and variable costs associated with the assignment of activities to designs.

The following review of the relevant literature starts with the classical assignment problem and leads to the formulation of problem (P). Different authors have used various terminologies in describing relevant formulations. In the following discussion, the original terminologies are used, and are followed by our equivalent terminology, where appropriate, shown in parenthesis.

1.1 Generalized Assignment Problem

In a classical assignment problem [Hillier and Lieberman (1980)], the purpose is to find optimal pairs of agents and tasks or activities. Each task is assigned to a single agent, and each agent is given a single task, and the suitability of a particular set of assignments is determined by a single criterion function such as minimization of cost. In a generalized assignment problem (GAP), several tasks can be assigned each agent, subject to the resources available to the various agents [Ross and Soland (1975)], e.g., assigning software development tasks to programmers and assigning jobs to computers in a computer network.

A variety of well-known facility location and location-allocation problems have been shown to be equivalent to, and therefore solvable as GAP's [Ross and Soland (1977)]. Here, in general, the tasks represent demand centers for a good or service, and the agents represent supply centers to be established at potential sites or locations. Each demand center must be supplied from a supply center. A fixed cost is incurred for each supply center established, and, in addition, there is a cost incurred for each unit processed at a supply center and transportation costs incurred for the units sent from supply centers to demand centers. The problem may be "uncapacitated" -- when there is no limit to the number of units that may be processed by

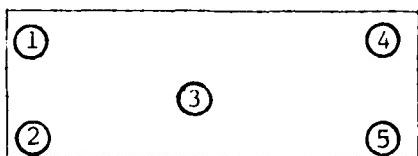
a supply center, or "capacitated" -- when there are restrictions on the number of units that may be processed. The objective is to select supply center locations and set up a distribution assignment so that the total cost is minimized.

1.2 Multiactivity Multifacility Uncapacitated Assignment Problem

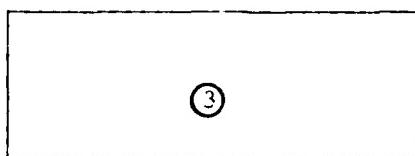
A salient feature of the above facility location problems is that each demand center (activity) is assigned to a single supply center (facility). Sometimes, however, it may be desirable to assign an activity to more than one facility. This leads to the concept of "design," and the multiactivity multifacility assignment problem [Pinkus, Gross, and Soland (1973)]. Before describing such a problem, some terminology is considered first.

A design involves the use of one or more facilities, and represents a meaningful configuration of facilities along with a meaningful strategy for using them -- as illustrated in the following examples.

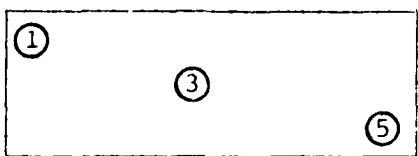
Consider five facilities and their locations as shown in Figure 1(a). (From practical considerations, these may be existing and/or potential locations.) Three of the possible designs are shown in Figures 1(b) to 1(d). Design 1 is completely centralized since it uses only one facility, whereas design 3 is completely decentralized since it uses all the facilities.



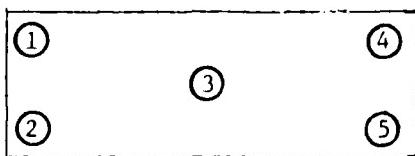
(a) Locations for five facilities



(b) Design 1: one facility--location (3)



(c) Design 2: three facilities--locations (1), (3), (5)



(d) Design 3: five facilities--all locations

Figure 1. Examples of alternate designs for a system of five facilities

It is possible for several designs to have the same facilities but different configuration and strategies for using these facilities, e.g., a multiproduct multi-echelon inventory system [Gross, Pinkus, and Soland (1979)]. Figure 2(a) shows design 1 containing certain facilities (warehouses) at the central, regional, and local levels or echelons. Figure 2(b) shows design 2 with the same facilities but having a different configuration.

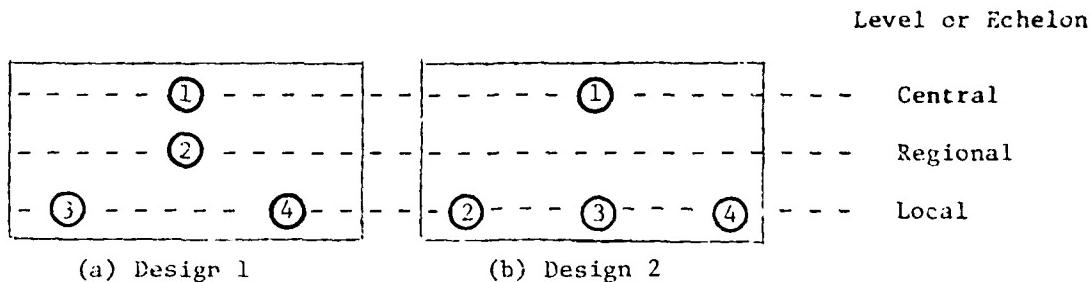


Figure 2. Example of alternative designs having the same facilities but different configuration

The distribution of a given activity at various facilities under design 1 would be different than under design 2, depending, of course, on the inventory policies. This results in different variable costs (described later) for that activity under design 1 as against design 2. In fact, it is possible to have a situation where two or more designs have the same facilities and the same configuration but different strategies, resulting in different variable costs. For example, one strategy might specify an equal distribution of a specific activity over the various facilities, whereas another strategy could impose a different distribution scheme over the same facilities.

In general, if a system is to be composed of at most p facilities, the number of alternative designs is $2^p - 1$ if no two designs have the same facilities. However, with the same facilities but different configurations and strategies, the number of alternative designs could be much higher. In practice, it is possible to eliminate a majority of alternative designs because of geographical, political, economical, and other factors.

The multiactivity multifacility assignment problem seeks minimization of some measure of total system cost such as, total expected cost over a given time period or total discounted cost over the lifetime of the system. The system cost will include investment costs for building or leasing the system, operating costs for operation and maintenance of the system, and the costs for providing necessary services. Both the investment costs and the operating costs have fixed as well as variable components [Ross and Soland (1980)]. The fixed components include those costs associated with the facilities of a given design which are independent of the activities served. Such costs are called fixed costs. On the other hand, the variable components and the service costs include those costs which are completely dependent on the service demand of the activities at the various facilities in a given design. Such costs are called variable costs. By definition, both the fixed costs and the variable costs are relative terms.

An equivalent formulation of the multiactivity multifacility assignment problem defined by Pinkus, Gross, and Soland (1973) is as follows.

Let a_{ij} = variable cost of activity j using design i
($i=1, \dots, m$; $j=1, \dots, n$)

b_k = fixed cost of facility k ($k=1, \dots, p$)

$b_{ik} = 1$ if facility k is included in design i ,
= 0 otherwise.

The decision variable x_{ij} is defined as:

$$x_{ij} = 1 \text{ if activity } j \text{ uses design } i , \\ = 0 \text{ otherwise.}$$

Then, the uncapacitated assignment problem called problem (PU) is to find x_{ij} values that:

$$\left\{ \begin{array}{l} \text{Minimize} \quad \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k u \left(\sum_{i=1}^m b_{ik} \sum_{j=1}^n x_{ij} \right) \\ \text{subject to} \quad \sum_{i=1}^m x_{ij} = 1 \quad \text{for } j=1, \dots, n \\ \qquad \qquad \qquad x_{ij} = 0 \text{ or } 1 \text{ for all } i \text{ and } j \\ \text{where} \quad u(\cdot) = 0 \text{ if } (\cdot) \leq 0 , \\ \qquad \qquad \qquad = 1 \text{ if } (\cdot) > 0 . \end{array} \right. \quad \begin{array}{l} (1) \\ (2) \\ (3) \end{array}$$

The objective function of this problem consists of two distinct parts. The first part represents the total variable cost, and the second, the total fixed cost of the system. Constraints (2) and (3) ensure that each activity is assigned to a single design. Of course, the optimal solution may involve the use of more than one design.

Problem (PU) is a 0-1 nonlinear programming problem (because of the step function u), and a branch-and-bound algorithm using linear underestimates for the nonlinear part of the objective function has been described in Pinkus, Gross, and Soland (1973). A heuristic procedure for this problem is given by Khumawala and Stinson (1980) in an unpublished paper. This procedure is an extension of some earlier work [Khumawala (1973)].

1.3 Adding Capacity Constraints -- Problem (P)

A weakness of problem (PU) is that it assumes unlimited capacity available at each facility in terms of the activities using a given facility. In practice, a facility may not have the capability to serve every activity, and may have restrictions as to the total capacity available to handle more than one activity.

Let s_k = capacity available at facility k , and

d_{ijk} = capacity required at facility k for activity j
when activity j uses design i .

If design i does not include facility k , then $d_{ijk} = 0$ for all j .

Define the decision variable y_k as:

$y_k = 1$ if facility k is used,
 $= 0$ otherwise.

Then the assignment problem [Gross, Pinkus, and Soland (1979)],
called problem (P) is to find x_{ij} and y_k values that:

$$\text{Minimize } \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k y_k \quad (4)$$

$$(P) \quad \text{subject to } \sum_{i=1}^m x_{ij} = 1 \quad j=1, \dots, n \quad (2)$$

$$\sum_{i=1}^m \sum_{j=1}^n d_{ijk} x_{ij} \leq s_k y_k \quad k=1, \dots, p \quad (5)$$

$$x_{ij}, y_k = 0 \text{ or } 1 \text{ for all } i, j, k \quad (6)$$

Constraints (5) of problem (P) ensure that the capacities available at the facilities are not violated. Problem (P) is, thus, a multiactivity multifacility capacity-constrained 0-1 assignment problem, as compared to problem (PU) which is uncapacitated. In problem (P), constraints (2) along with the part of constraints (6) involving the x_{ij} 's ensure that each activity is assigned to a single design. Of course, the optimal solution may result in the use of more than one design.

For an example of five facilities and three designs as shown in Figures 1(b) to 1(d), and four activities; the matrix $[a_{ij} | b_k | d_{ijk}]$ is as shown in Figure 3.

1.3.1 Comparison with the uncapacitated assignment problem.

Comparison of the capacitated problem (P) with the uncapacitated problem (PU) shows that the objective functions (1) and (4) are equivalent and constraints (2) in each are the same. Constraints (5) serve to impose the capacity constraints and at the same time, for a given design, the relevant facilities are forced in the solution. For an

		Variable Costs (a_{ij})				Fixed Costs (b_k)				Capacities Required (d_{ijk})			
										e.g., for $k=1^*$			
		Activities (j)				Facilities (k)				Activities (j)			
Designs (i)	1	1	2	3	4	1	2	3	4	5	1	1	2
	2	a_{11}	a_{12}	a_{13}	a_{14}	b_3					0	0	0
	3	a_{21}	a_{22}	a_{23}	a_{24}	b_1	b_3	b_5			d_{211}	d_{221}	d_{231}
		a_{31}	a_{32}	a_{33}	a_{34}	b_1	b_2	b_3	b_4	b_5	d_{311}	d_{321}	d_{331}

Figure 3.

Matrix of variable costs, fixed costs, and capacities required -- example

*Similar d_{ijk} values exist for $k=2, \dots, 5$ depending on the inclusion of the facility in a design.

x_{ij} equal to 1, all the facilities with $d_{ijk} > 0$ must have y_k values equal to 1 in order to satisfy (5) and the corresponding fixed costs b_k are therefore included in (4). If $y_k = 0$ and $d_{ijk} > 0$, then x_{ij} must be 0 in order to satisfy (5).

Problem (P) has been formulated as a 0-1 linear programming problem whereas problem (PU) was formulated as a 0-1 nonlinear programming problem.

Note that problem (PU) can be easily obtained as a special case of problem (P) by letting d_{ijk} equal 1 (for all j) if design i uses facility k , and setting all s_k equal to n . In other words, the corresponding formulation is to find x_{ij} and y_k values that:

$$\left\{ \begin{array}{l} \text{Minimize} \quad \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k y_k \\ \text{subject to} \quad \sum_{i=1}^m x_{ij} = 1 \quad j=1, \dots, n \\ \quad \sum_{i=1}^m e_{ik} \sum_{j=1}^n x_{ij} \leq n y_k \quad k=1, \dots, p \\ \quad x_{ij}, y_k = 0 \text{ or } 1 \text{ for all } i, j, k \\ \text{where} \quad e_{ik} = 1 \text{ if design } i \text{ uses facility } k, \\ \quad \quad \quad = 0 \text{ otherwise.} \end{array} \right. \quad \begin{array}{l} (4) \\ (2) \\ (7) \\ (6) \end{array}$$

1.3.2 Comparison with the fixed-charge location-allocation problem.

Problem (P) bears a resemblance to the well-known fixed-charge location-allocation problem or capacitated facility location problem [Geoffrion (1975); Ross and Soland (1977)]. There are, however, very significant differences between the two. In order to point out these differences, here is a statement of the location-allocation problem (LA) as given by Gross, Pinkus, and Soland (1979) in a form

similar to that of problem (P).

Find x_{kj} and y_k values that

$$\left\{ \begin{array}{l} \text{Minimize} \quad \sum_{k=1}^p \sum_{j=1}^n a_{kj} x_{kj} + \sum_{k=1}^p b_k y_k \\ \text{subject to} \quad \sum_{k=1}^m x_{kj} = 1 \quad j=1, \dots, n, \\ \quad \sum_{j=1}^n d_j x_{kj} \leq s_k y_k \quad k=1, \dots, p \end{array} \right. \quad (8)$$

$$(LA) \quad \left\{ \begin{array}{l} \text{subject to} \quad \sum_{k=1}^m x_{kj} = 1 \quad j=1, \dots, n, \\ \quad \sum_{j=1}^n d_j x_{kj} \leq s_k y_k \quad k=1, \dots, p \end{array} \right. \quad (9)$$

$$\left. \begin{array}{l} x_{kj} \geq 0, y_k = 0 \text{ or } 1 \text{ for all } j \\ \text{and } k \end{array} \right. \quad (11)$$

Here x_{kj} represents the fraction of customer (activity) j 's demand that is supplied by a facility at location k .

The most important distinction between problem (LA) and problem (P) is the relationship between assignments and facilities. In problem (LA) there is a direct connection between the assignments made and the facilities required, and each assignment affects only one facility, i.e., the assignment $x_{kj} > 0$ has a bearing on only one of the constraints (10) and, therefore, on only one variable y_k . On the other hand, in problem (P), the connection between the assignments made and the facilities required is indirect, and each assignment can affect several facilities, i.e., the assignment $x_{ij} = 1$ bears on all of the constraints (5) for which $d_{ijk} > 0$ and, therefore, on several variables y_k .

Another distinction is the relative difficulty of the two problems. While problem (LA) is not easy to solve, branch-and-bound approaches have been successful in dealing with it because once values are specified for the y_k , the x_{jk} are found by solving a transportation problem. Problem (LA) becomes more difficult if the constraints $x_{kj} \geq 0$ in (10) are replaced by $x_{kj} = 0$ or 1 in order to preclude supply of customer (activity) j 's demand by more than one facility. With this change,

problem (LA) may be treated as a generalized assignment problem and is solvable using an efficient branch-and-bound algorithm [Ross and Soland (1977)]. Problem (P) is more difficult than this variation of problem (LA) because of the above stated indirect connection between the assignments and the facilities. Even after values have been specified for all the y_k , problem (P) remains a difficult 0-1 linear programming problem because of the interaction of the constraints.

1.3.3 Solving problem (P).

The capacitated problem (P) has $mn+p$ 0-1 variables and $n+p$ constraints, so the problem dimensions may be large from practical considerations. For example, with $m=n=30$ and $p=20$, problem (P) has 920 variables and 50 constraints. The 0-1 LP computer codes generally available are limited in terms of problem size. For example, the code used by Gross, Pinkus, and Soland (1979) can handle up to 40 variables and 20 constraints. A better and more efficient code [Geoffrion and Nelson (1968)] allows up to 90 variables and 50 constraints. This fact, together with the structure of problem (P) suggests that a specialized algorithm could be developed that would be more efficient for practical problems than the general integer linear programming algorithms (on which the available codes are based).

With the above background in mind, the development of the solution algorithm and the computer program to solve problem (P) was undertaken and is described in Chapters 2 through 4.

1.4 Areas of Application

The solution algorithm and the computer program are designed to solve a multiactivity multifacility capacity-constrained 0-1 assignment problem, i.e., one which can be formulated as problem (P).

The basic elements of such a problem are activities that must be assigned, facilities and their meaningful configurations

represented as designs, the fixed and variable costs, and the capacity requirements of the activities.

The formulation (P) applies to existing and/or proposed facilities. In other words, it is useful for a situation where the decision may be to delete some of the existing facilities, as well as for a situation where the decision involves a selection out of a set of proposed facilities.

Table 1 includes examples of areas where formulation (P) is applicable. Within each application area, activities and facilities are identified. The implications of designs, variable costs, and fixed costs are apparent.

Obtaining the values of the data elements b_k , d_{ijk} , s_k , and in particular a_{ij} , can be a simple or a complex exercise depending on the particulars of the application, and the nature of the components comprising these elements. For example, in designing multi-echelon inventory systems [Gross, Pinkus, and Soland (1979)], a_{ij} represents the inventory cost of product (activity) j using echelon structure (design) i and b_k represents the fixed cost of installation (facility) k . The inventory cost a_{ij} includes the cost of procurement, carrying inventory, filling orders, and stockouts. The value a_{ij} , and associated inventory stockage policies, are arrived at by solving a multi-echelon inventory problem. In other words, for product j stocked under echelon structure i , optimal inventory policies are determined, at each installation of the structure, which yields a_{ij} . The facility fixed cost b_k includes the capital expenditure for building the installation, along with a number of fixed costs associated with operating it, such as administrative expenses, the expense of renting the facility (if it is not built), and certain other fixed operating expenses.

In the case of designing a support system for repairable

TABLE 1
EXAMPLES OF APPLICATION AREAS

Area of Application	Activities	Facilities
1. Design of multi-echelon inventory systems*	Types of items to be stocked	Warehouses (Comprising different levels or echelons, e.g., central, regional, and local warehouses)
2. Assignment of repairable components**	Major components of a unit, e.g., components of an aircraft, a ship, a piece of machinery	Repair depots
3. Design of training programs	Training program categories or occupational classifications	Training schools
4. Location of facilities***	Types of services, e.g., health-care services	Buildings or installations, e.g., health-care centers

* Gross, Pinkus, and Soland (1979)

**Gross and Pinkus (1979)

***Pinkus, Gross, and Soland (1973)

items [Gross and Pinkus (1979)], a_{ij} represents the total variable cost if unit type (activity) j is repaired under design i . The set of parameters taken into consideration to compute this cost for each unit type includes such things as varying population sizes, failure rates, average repair times, costs associated with their repair, the purchase and storage of spares, the purchase of repair channels, and travel to depots (facilities) for repair. A computer program is used to solve a spares and server provisioning problem, and the results provide the basic information to compute a_{ij} .

Thus, in general, the data elements of problem (P) may be obtained directly and/or by solving other related problem(s); it depends on the definition and the nature of the components comprising these data elements for a specific application area.

2. DEVELOPMENT OF THE SOLUTION ALGORITHM

The solution algorithm that has been developed to solve problem (P) is a branch-and-bound procedure which makes use of Lagrangian relaxation as a basic step.

This chapter considers two different Lagrangian relaxations of problem (P), their general characteristics, and some useful results leading to the specific case of Lagrangian relaxation utilized in the solution algorithm.

2.1 Lagrangian Relaxation

Taking a set of "complicating" constraints of a general mixed-integer program into the objective function in a Lagrangian fashion (with fixed multipliers) results in a "Lagrangian relaxation" of the original problem [Geoffrion (1974)]. The relaxed problem is easy to solve compared to the original problem, and provides a lower bound (for minimization problems) on the optimal value of the original problem.

Although the use of Lagrangian relaxation in discrete optimization has been reported prior to 1970 [e.g., Lorie and Savage (1955), Everett (1963), and Gilmore and Gomory (1963)], the "birth" of the Lagrangian approach as it exists today [Fisher (1978)] occurred in 1970 with the successful application of Lagrangian relaxations to the traveling salesman problem [Held and Karp (1970, 1971)]. This was followed by application of Lagrangian relaxation to scheduling problems [Fisher and Schrage (1972), and Fisher (1973, 1976)], the general integer programming problem [Shapiro (1971), and Fisher and Shapiro (1974)] and the generalized assignment problem [Ross and Soland (1975)]. Table 2 lists the applications of Lagrangian relaxation as given by Fisher (1978). A review of Lagrangian relaxation is also provided by Shapiro (1977) and Christofides (1980).

TABLE 2
APPLICATIONS OF LAGRANGIAN RELAXATION*

Problem	Researchers	Lagrangian Problem
TRAVELING SALESMAN		
Symmetric	Held & Karp (1970, 1971)	Spanning Tree
Asymmetric	Bazarras & Goode (1977)	Spanning Tree
Symmetric	Balas & Christofides (1976)	Perfect 2-Matching
Asymmetric	Balas & Christofides (1976)	Assignment
SCHEDULING		
$n m$ Weighted Tardiness	Fisher (1973)	Pseudo-Polynomial
1 Machine Weight Tardiness	Fisher (1976)	Dynamic Programming
Power Generation Systems	Muckstadt & Koenig (1977)	Pseudo-Polynomial DP
GENERAL IP		
Unbounded Variables	Fisher & Shapiro (1974)	Group Problem
Unbounded Variables	Burdet & Johnson (1976)	Group Problem
0 - 1 Variables	Etcheberry, et. al. (1978)	0 - 1 GUB
LOCATION		
Uncapacitated	Cornuejols, Fisher, & Nemhauser (1977)	0 - 1 VUB
Capacitated	Geoffrion & McBride (1977)	0 - 1 VUB
Databases in Computer Networks	Fisher & Hochbaum (1978)	0 - 1 VUB
GENERALIZED ASSIGNMENT		
	Ross & Soland (1975)	Knapsack
	Chalmet & Gelders (1976)	Knapsack, 0-1 GUB
SET COVERING--PARTITIONING		
Covering	Etcheberry (1977)	0 - 1 GUB
Partitioning	Nemhauser & Weber (1978)	Matching

*Source: Fisher (1978)

2.1.1 Relaxing Problem (P)

By dividing constraints (5) by s_k and letting $r_{ijk} = d_{ijk}/s_k$, problem (P) can be restated as follows.

$$(P) \left\{ \begin{array}{l} \text{Minimize} \quad \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k y_k \\ \text{subject to} \quad \sum_{i=1}^m x_{ij} = 1 \quad j=1, \dots, n \\ \quad \sum_{i=1}^m \sum_{j=1}^n r_{ijk} x_{ij} \leq y_k \quad k=1, \dots, p \\ \quad x_{ij}, y_k = 0 \text{ or } 1 \quad \text{for all } i, j, k \end{array} \right. \quad \begin{array}{l} (4) \\ (2) \\ (5') \\ (6) \end{array}$$

A Lagrangian relaxation (LR_u) of problem (P) relative to constraints (2) is obtained as

$$(LR_u) \left\{ \begin{array}{l} \text{Minimize} \quad \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k y_k - \sum_{j=1}^n u_j \left(\sum_{i=1}^m x_{ij} - 1 \right) \\ \text{subject to} \quad \sum_{i=1}^m \sum_{j=1}^n r_{ijk} x_{ij} \leq y_k \quad k=1, \dots, p \\ \quad x_{ij}, y_k = 0 \text{ or } 1 \quad \text{for all } i, j, k \end{array} \right. \quad \begin{array}{l} (12) \\ (5') \\ (6) \end{array}$$

where the u_j are Lagrange multipliers; it follows that the optimal value of problem (LR_u) is a lower bound on the optimal value of problem (P), i.e., $Z(LR_u) \leq Z(P)$. We will continue to use this notation in which $Z(\cdot)$ is the optimal value of problem (\cdot) .

Another Lagrangian relaxation (LR_v) of problem (P), relative to constraints (5'), is obtained as

$$\text{Minimize}_{i,j} \quad \sum_{i,j} a_{ij} x_{ij} + \sum_k b_k y_k - \sum_k v_k \left(y_k - \sum_{i,j} x_{ij} r_{ijk} \right)$$

subject to (2) and (6), or equivalently,

$$(LR_v) \left\{ \begin{array}{ll} \text{Minimize}_{i,j} & \sum_{i,j} x_{ij} \left(a_{ij} + \sum_k v_k r_{ijk} \right) - \sum_k y_k \left(v_k - b_k \right) \\ \text{subject to} & \sum_i x_{ij} = 1 \quad j=1, \dots, n \\ & x_{ij}, y_k = 0 \text{ or } 1 \quad \text{for all } i, j, k \end{array} \right. \quad (13)$$

$$(2)$$

$$(6)$$

where the v_k are non-negative Lagrange multipliers; it follows that $Z(LR_v) \leq Z(P)$.

2.1.2 General Characteristics

A Lagrangian relaxation provides a lower bound on the optimal value of the original problem, i.e., in our case $Z(LR_u) \leq Z(P)$ and $Z(LR_v) \leq Z(P)$. The usefulness of a Lagrangian relaxation depends on the closeness of this lower bound to the optimal value of the original problem. However, the relaxation must be "easy" to solve relative to the original problem. We observe that the optimal value of y_k in problem (Lk_v) is 1 if $(v_k - b_k) \geq 0$ and 0 if $(v_k - b_k) \leq 0$, and then problem (LR_v) reduces to n 0-1 "multiple choice" problems which are very easy to solve. On the other hand, problem (LR_u) reduces to k 0-1 knapsack problems. However, these problems are not independent because of the interaction of constraints (5') and the indirect relationship described earlier in Section 1.3 between the assignments and the facilities. In view of this complexity, relaxation (LR_u) will not be considered further.

The choice of Lagrange multipliers in relaxation (LR_v) should be such that $Z(LR_v)$ is as large as possible and hence as close as possible to $Z(P)$ in view of the relationship $Z(LR_v) \leq Z(P)$. In other words, an equivalent problem is to find a vector v (representing v_1, v_2, \dots, v_k) to

$$(P) \quad \left\{ \begin{array}{l} \text{Maximize } [Z(LR_v)] \\ v \geq 0 \end{array} \right. \quad (14)$$

Obviously, $Z(LR_v) \leq Z(D) \leq Z(P)$.

The general properties of Lagrangian relaxation have been well described in the literature [e.g., Geoffrion (1974), Geoffrion and McBride (1978), and Fisher (1980)]. Some of these properties relating the Lagrangian relaxation and the usual LP relaxation are stated below.

The LP relaxation (\bar{P}) of problem (P) is obtained by relaxing the integrality constraints (6), i.e., the formulation (\bar{P}) is

$$\left\{ \begin{array}{ll} \text{Minimize} & \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k y_k \\ \text{subject to} & \sum_{i=1}^m x_{ij} = 1 \quad j=1, \dots, n \\ & \sum_{i=1}^m \sum_{j=1}^n r_{ijk} x_{ij} \leq y_k \quad k=1, \dots, p \\ & y_k \leq 1 \quad k=1, \dots, p \\ & x_{ij}, y_k \geq 0 \quad \text{for all } i, j, k \end{array} \right. \quad \begin{array}{l} (4) \\ (2) \\ (5') \\ (15) \\ (16) \end{array}$$

Note that the constraints $x_{ij} \leq 1$ are implicit in constraints (2).

Also consider the following partial convex hull relaxation (P^*) of problem (P) .

$$\left\{ \begin{array}{ll} \text{Minimize} & \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_{ij} + \sum_{k=1}^p b_k y_k \\ \text{subject to} & \sum_{i=1}^m \sum_{j=1}^n r_{ijk} x_{ij} \leq y_k \quad k=1, \dots, p \\ & x_{ij}, y_k \in \text{convex hull } \{(2), (6)\} \end{array} \right. \quad \begin{array}{l} (4) \\ (5') \\ (17) \end{array}$$

Then the relationships between the optimal values of various problems [Geoffrion and McBride (1978)] are as follows.

$$Z(\bar{P}) \leq Z(LR_v^*) \leq \max_{v \geq 0} Z(LR_v) = Z(D) = Z(P^*) \leq Z(P) \quad (18)$$

where \hat{v} are the values $\hat{v}_1, \hat{v}_2, \dots, \hat{v}_p$ of a dual optimal solution of (\bar{P}) corresponding to constraints (5').

Thus, the optimal dual solution associated with the usual LP relaxation furnishes a choice of Lagrange multipliers such that the associated Lagrangian relaxation is at least as tight as the usual LP relaxation, and generally a good deal tighter and even as tight as the partial convex hull relaxation.

Since $Z(D) = Z(P^*)$, the quality of the bound obtained from the Lagrangian relaxation depends on where $Z(P^*)$ lies in the range between $Z(\bar{P})$ and $Z(P)$. It turns out that problem (LR_v) possesses the "integrality property," i.e., the optimal value of problem (LR_v) is not altered by dropping the integrality conditions on its variables and therefore [Geoffrion (1974)]

$$Z(D) = Z(P^*) = Z(\tilde{P}) \quad (19)$$

Thus, the Lagrangian relaxation (LR_v) is no better than the LP relaxation (\bar{P}) . On the other hand, Lagrangian relaxation (LR_u) does not possess the integrality property and, hence, could provide an equal or better bound than the LP relaxation (\bar{P}) ; but the computational difficulties do not favor pursuing formulation (LR_u) .

It is possible to consider alternative formulations of problem (P) with the objective of obtaining tighter bounds. This aspect is discussed in Chapter 6.

2.2 Some Results

We now turn to the basic question of choosing Lagrange multipliers v so that (LR_v) is optimal to the extent possible, which is equivalent to solving problem (D). We also need to consider this question when some of the x_{ij} and y_k variables have been assigned values of 1 or 0, i.e., at a node other than the starting or "root" node in the branch-and-bound tree. For this purpose, some terminology is defined and formulations corresponding to problems (P), (LK_v) and (D) are first developed. Then some important results pertaining to the choice of Lagrange multipliers will be proved. Gavish (1978) provides a method of obtaining the 'best' multipliers, based on solving an equivalent linear programming problem. Such a formulation is difficult in our case, and, besides, we propose to avoid solving LP problems in our branch-and-bound procedure.

Define the sets

$$S = \{(i,j) | x_{ij} \text{ has an assigned value of 1 or 0}\}, \text{ and}$$

$$T = \{k | y_k \text{ has an assigned value of 1 or 0}\}.$$

These sets represent the partial solution of problem (P) and the variables contained in these sets are termed fixed variables. [Geoffrion (1967)]. Let \bar{S} and \bar{T} represent the corresponding complementary sets, i.e., comprised of the x_{ij} and y_k variables, which have not been assigned specific values and, therefore, are called free variables. A completion of a partial solution is defined as a solution that is determined by S and T together with a binary specification (0 or 1) of the values of the free x_{ij} and y_k variables from sets \bar{S} and \bar{T} .

$$\text{Let } S \cup \bar{S} = S_1 \text{ and } T \cup \bar{T} = T_1.$$

Consider a partial solution to problem (P) in which specific values (of 1 or 0) are assigned to some of the x_{ij} and y_k such that

$$\sum_{\substack{i=1 \\ (i,j) \in S}}^m x_{ij} \leq 1 \quad \forall j,$$

$$\text{and } \sum_{\substack{i \ j \\ (i,j) \in S}} r_{ijk} x_{ij} \leq y_k \quad \forall k \in T$$

$$\sum_{\substack{i \ j \\ (i,j) \in \bar{S}}} r_{ijk} x_{ij} \leq 1 \quad \forall k \in \bar{T}$$

and such that $x_{ij} = 1$ and $e_{ik} = 1$ imply that $k \in T$ and $y_k = 1$.

Recall that, by definition, $e_{ik} = 1$ if design i uses facility k ,

and $e_{ik} = 0$ otherwise.

The problem of finding an optimal completion of the partial solution of problem (P) can be stated as follows.

$$(P_\ell) \left\{ \begin{array}{l} \text{Minimize} \quad \sum_{\substack{i \ j \\ (i,j) \in \bar{S}}} a_{ij} x_{ij} + \sum_{k \in \bar{T}} b_k y_k + \sum_{\substack{i \ j \\ (i,j) \in S}} a_{ij} x_{ij} + \sum_k b_k y_k \quad (20) \\ \text{subject to} \quad \sum_{\substack{i \\ (i,j) \in \bar{S}}} x_{ij} = 1 - \sum_{\substack{i \\ (i,j) \in S}} x_{ij} \quad \forall j \quad (21) \\ \quad \sum_{\substack{i \ j \\ (i,j) \in \bar{S}}} r_{ijk} x_{ij} \leq y_k - \sum_{\substack{i \ j \\ (i,j) \in S}} r_{ijk} x_{ij} \quad \forall k \quad (22) \\ \quad x_{ij}, y_k = 0 \text{ or } 1 \quad \forall (i,j) \in \bar{S}, k \in \bar{T} \quad (23) \end{array} \right.$$

We call this problem (P_ℓ) where ℓ indicates the node in the branch-and-bound tree.

A Lagrangian relaxation of problem (P_ℓ) with respect to constraints (22) is obtained by introducing non-negative Lagrange multipliers v_k , $k=1, 2, \dots, p$; the relaxation is then

$$\begin{aligned}
 \text{Minimize} \quad & \sum_{\substack{i \\ (i,j) \in \bar{S}}} \sum_{j} a_{ij} x_{ij} + \sum_{k \in \bar{T}} b_k y_k + \sum_{\substack{i \\ (i,j) \in S}} \sum_{j} a_{ij} x_{ij} + \sum_{k \in T} b_k y_k \\
 & - \sum_k v_k \left[y_k - \sum_{\substack{i \\ (i,j) \in \bar{S}}} \sum_j r_{ijk} x_{ij} - \sum_{\substack{i \\ (i,j) \in S}} \sum_j r_{ijk} x_{ij} \right] \quad (24)
 \end{aligned}$$

$$\begin{aligned}
 \text{subject to} \quad & \sum_{\substack{i \\ (i,j) \in \bar{S}}} x_{ij} = 1 - \sum_{\substack{i \\ (i,j) \in S}} x_{ij} \quad \forall j \quad (21)
 \end{aligned}$$

$$x_{ij}, y_k = 0 \text{ or } 1 \quad \forall (i,j) \in \bar{S}, k \in \bar{T} \quad (23)$$

Rearranging (24), and using the relationship $T_1 = T \cup \bar{T}$, we have problem

$$\left\{ \begin{array}{ll}
 \text{Minimize} & \sum_{\substack{i \\ (i,j) \in \bar{S}}} \sum_j x_{ij} \left(a_{ij} + \sum_{k \in T_1} v_k r_{ijk} \right) + \sum_{\substack{i \\ (i,j) \in S}} \sum_j x_{ij} \left(a_{ij} + \sum_{k \in T_1} v_k r_{ijk} \right) \\
 & - \sum_{k \in \bar{T}} y_k \left(v_k - b_k \right) - \sum_{k \in T} y_k \left(v_k - b_k \right) \quad (25) \\
 \text{subject to} & \sum_{\substack{i \\ (i,j) \in \bar{S}}} x_{ij} = 1 - \sum_{\substack{i \\ (i,j) \in S}} x_{ij} \quad \forall j \quad (21) \\
 & x_{ij}, y_k = 0 \text{ or } 1 \quad \forall (i,j) \in \bar{S}, k \in \bar{T} \quad (23)
 \end{array} \right.$$

Then we have $Z(LR_{\lambda, v}) \leq Z(P_\lambda)$. An important problem is the choice of Lagrange multipliers v_1, v_2, \dots, v_p , represented by vector v , that maximizes $Z(LR_{\lambda, v})$, i.e., the problem (D_λ) :

$$(D_\lambda) \left\{ \begin{array}{l}
 \text{Maximize} [Z(LR_{\lambda, v})] \\
 v \geq 0
 \end{array} \right. \quad (26)$$

We now state and prove some theorems related to the choice of Lagrange multipliers v_1, v_2, \dots, v_p .

Theorem 1: There exists an optimal solution to problem (D) in which $v_k \geq b_k$ for all k .

Proof: Suppose $v_1 < b_1$, in an optimal solution to problem (D), i.e., $Z(D) = Z(LR_{v^*})$ where $v_1^* < b_1$.

Recall that

$$Z(LR_{v^*}) = \text{Min} \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k v_k^* r_{ijk} \right) - \sum_k y_k (v_k^* - b_k)$$

$$\text{s.t. } \sum_i x_{ij} = 1 \quad \forall j \quad (2)$$

$$x_{ij}, y_k = 0 \text{ or } 1 \quad \forall i, j, k \quad (6)$$

For $v_1^* < b_1$, the optimal value of y_1 is 0, and the term $-y_1(v_1^* - b_1)$ in the objective function is 0.

Consider what happens if we increase v_1^* to b_1 . Call the resulting vector \underline{v} . Consider problem $(LR_{\underline{v}})$. The optimal value of y_1 in problem $(LR_{\underline{v}})$ is 0 or 1, and the term $-y_1(v_1 - b_1)$ is 0. However, the optimal value of y_k is the same in problems (LR_{v^*}) and $(LR_{\underline{v}})$ for all $k > 1$. Therefore, the quantity $\sum_k y_k (v_k - b_k)$ is the same at the optimal solution for both $v = v^*$ and $v = \underline{v}$.

Since $\underline{v}_1 > v_1^*$, we note that in the objective function,

$$a_{ij} + \sum_{k=1}^p \underline{v}_k r_{ijk} \geq a_{ij} + \sum_{k=1}^p v_k^* r_{ijk} \quad \forall i, j,$$

and therefore $Z(LR_{\underline{v}}) \geq Z(LR_{v^*})$.

It follows that there is an optimal solution to problem (D) in which $v_1 \geq b_1$.

Since the choice of $k=1$ was arbitrary, the same result holds for any value of k , $k=1, \dots, p$; hence, there exists an optimal solution to problem (D) in which $v_k \geq b_k$ for all k .

Theorem 2: There exists an optimal solution to problem (D_λ) in which $v_k \geq b_k$ if (i) $k \in \bar{T}$ or (ii) $k \in T$ and $y_k = 0$.

Proof: Suppose $v_1 < b_1$ in an optimal solution to problem (D_λ) , i.e., $Z(D_\lambda) = Z(LR_\lambda, v^*)$ where $v_1^* < b_1$. Then $k=1$ can be such that $k \in T$ or $k \in \bar{T}$.

Case (i): Let $k \in \bar{T}$.

Recall that

$$\begin{aligned} Z(LR_\lambda, v^*) = \min_{(i,j) \in \bar{S}} & \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k v_k^* r_{ijk} \right) \\ & + \sum_{(i,j) \in S} x_{ij} \left(a_{ij} + \sum_k v_k^* r_{ijk} \right) \\ & - \sum_{k \in \bar{T}} y_k (v_k^* - b_k) - \sum_{k \in T} y_k (v_k^* - b_k) \end{aligned}$$

$$\text{s.t. } \sum_{(i,j) \in \bar{S}} x_{ij} = 1 - \sum_{(i,j) \in S} x_{ij} \quad \forall j \quad (21)$$

$$x_{ij}, y_k = 0 \text{ or } 1 \quad \forall (i,j) \in \bar{S}, k \in \bar{T} \quad (23)$$

For $v_1^* < b_1$, and $k \in \bar{T}$, the optimal value of y_1 is 0 and the term $-y_1(v_1^* - b_1)$ in the objective function is 0.

Let v_1^* be increased to b_1 ; call the resulting vector \underline{v} .

Consider problem $(LR_{\lambda, \underline{v}})$. The optimal value of y_1 in $(LR_{\lambda, \underline{v}})$ is 0 or 1, then the term $-y_1(v_1 - b_1)$ is 0. For $k > 1$, the optimal value of y_k being the same in (LR_{λ, v^*}) and $(LR_{\lambda, \underline{v}})$, we find that $\sum_{k \in T_1} y_k(v_k - b_k)$ is the same at the optimal solution for both

$v = v^*$ and $v = \underline{v}$. But $\underline{v}_1 > v_1^*$; therefore

$$a_{ij} + \sum_{k \in T_1} v_k r_{ijk} \geq a_{ij} + \sum_{k \in T_1} v_k^* r_{ijk} \quad \forall (i, j) \in S \text{ and } (i, j) \in \bar{S}$$

Hence, $Z(LR_{\lambda, \underline{v}}) \geq Z(LR_{\lambda, v^*})$, wherefrom it follows that there is an optimal solution to (D_λ) in which $v_1 \geq b_1$. Since the choice of $k=1$ was arbitrary, the same results hold for any value of k , $k \in \bar{T}$. Hence, there exists an optimal solution to problem (D_λ) in which $v_k \geq b_k$ for all $k \in \bar{T}$.

Case (ii): Let $k \in T$ and $y_k = 0$

Considering problem (LR_{λ, v^*}) , for $k = 1$, $v_1^* < b_1$, and $y_1 = 0$, the term $-y_1(v_1^* - b_1)$ in the objective function is 0.

Increase v_1^* to b_1 and call the resulting vector \underline{v} . The term $-y_1(v_1 - b_1)$ is 0. For $k > 1$, the optimal values of y_k are the same in problems (LR_{λ, v^*}) and $(LR_{\lambda, \underline{v}})$. Therefore $\sum_{k \in T_1} y_k(v_k - b_k)$ is the same at the optimal solution for both $v = v^*$ and $v = \underline{v}$. Since $\underline{v}_1 > v_1^*$,

$$a_{ij} + \sum_{k \in T_1} v_k r_{ijk} \geq a_{ij} + \sum_{k \in T_1} v_k^* r_{ijk} \quad \forall (i, j) \in S \text{ and } (i, j) \in \bar{S}$$

Therefore $Z(LR_{\lambda, \underline{v}}) \geq Z(LR_{\lambda, v^*})$. It follows that there exists an optimal solution to (D_λ) in which $v_1 \geq b_1$. The choice of $k=1$ being arbitrary, the same results hold for any value of k , $k \in T$ and $y_k = 0$; which proves case (ii) of the Theorem.

It may be added that there is another possibility which complements case (ii) of Theorem 2, i.e., if $k \in T$ and $y_k = 1$. We treat this possibility as a conjecture since a result similar to the one above could not be proved, as discussed now.

With $y_1 = 1$ and $v_1^* < b_1$, we observe from problem (LR_{λ, v^*}) that for a solution vector X^* (with elements x_{ij}^*) and Y^* (with elements $y_1^*, \dots, y_p^* | y_1^* = 1$ and $y_2^*, \dots, y_p^* = 0$ or 1),

$$\begin{aligned} Z(LR_{\lambda, v^*}) &= \sum_{\substack{i \ j \\ (i, j) \in \bar{S}}} x_{ij}^* \left(a_{ij} + v_1^* r_{ij1} + \sum_{k>1} v_k^* r_{ijk} \right) \\ &\quad + \sum_{\substack{i \ j \\ (i, j) \in S}} x_{ij}^* \left(a_{ij} + v_1^* r_{ij1} + \sum_{k>1} v_k^* r_{ijk} \right) \\ &\quad - \sum_{k \in \bar{T}} y_k^* (v_k^* - b_k) - y_1 (v_1^* - b_1) - \sum_{\substack{k \in T \\ k \neq 1}} y_k^* (v_k^* - b_k) \end{aligned}$$

Since $v_1^* < b_1$ and $y_1 = 1$ the term $-y_1(v_1^* - b_1)$ is positive. If we raise v_1^* to b_1 , say \underline{v}_1 , the term $-y_1(\underline{v}_1 - b_1)$ is 0.

The difference between $Z(LR_{\lambda, \underline{v}})$ and the objective function value of problem $(LR_{\lambda, \underline{v}})$ with $X=X^*$ and $Y=Y^*$ is

$$\begin{aligned} &= \sum_{i \ j} x_{ij}^* v_1^* r_{ij1} + (b_1 - v_1^*) - \sum_{i \ j} x_{ij}^* b_1 r_{ij1} \\ &= (b_1 - v_1^*) - \sum_{i \ j} x_{ij}^* (b_1 - v_1^*) r_{ij1}. \end{aligned}$$

This difference can be either negative or positive, and so we cannot conclude that there is an optimal solution to problem (D_λ) in which

$v_1 \geq b_1$. We believe this conclusion to be false.

Theorem 3: Let (X^*, Y^*) solve problem (LR_v) for $v_k = b_k$ for all k . If (X^*, Y^*) is feasible for problem (P), there exists an optimal solution to problem (D) in which $v_k = b_k$ for all k .

Proof: In view of Theorem 1, there exists an optimal solution to (D) in which $v_k \geq b_k$ for all k , i.e., $v \geq b$. Let \underline{v} be such an optimal v . We will show that $Z(LR_{\underline{v}}) \leq Z(LR_b)$, from which it follows that $v = b$ solves problem (D).

Recall that

$$Z(LR_{\underline{v}}) = \min_{X, Y} \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k \underline{v}_k r_{ijk} \right) - \sum_k y_k (\underline{v}_k - b_k)$$

$$\text{s.t. } \sum_i x_{ij} = 1 \quad \forall j \quad (2)$$

$$x_{ij}, y_k = 0 \text{ or } 1 \quad \forall i, j, k \quad (6)$$

Since $\underline{v} \geq b$, $y_k = 1 \forall k$ is an optimal choice.

$$\text{Hence, } Z(LR_{\underline{v}}) = \min_{X} \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k \underline{v}_k r_{ijk} \right) - \sum_k \left(\underline{v}_k - b_k \right)$$

$$\text{s.t. } \sum_i x_{ij} = 1 \quad \forall j \quad (2)$$

$$x_{ij} = 0 \text{ or } 1 \quad \forall i, j \quad (6a)$$

Now consider (LR_b) . Since $v = b$, the last term of the objective function drops out, and we have

$$Z(LR_b) = \min_{X, Y} \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k b_k r_{ijk} \right)$$

subject to (2) and (6)

$$= \underset{X}{\text{Min}} \sum_{i,j} x_{ij}^* \left(a_{ij} + \sum_k b_k r_{ijk} \right)$$

subject to (2) and (6a)

$$= \sum_{i,j} x_{ij}^* \left(a_{ij} + \sum_k b_k r_{ijk} \right)$$

where X^* with elements x_{ij}^* is the minimizing solution vector which satisfies (2) and (6a).

Now (X^*, Y^*) feasible for (P) implies that

$$\sum_{i,j} x_{ij}^* r_{ijk} \leq y_k^* \leq 1 \quad \forall k.$$

$$\text{Hence, } \sum_k \left(\frac{v_k}{y_k} - b_k \right) \sum_{i,j} x_{ij}^* r_{ijk} \leq \sum_k \left(\frac{v_k}{y_k} - b_k \right),$$

$$\text{or } \sum_k \left(\frac{v_k}{y_k} - b_k \right) \sum_{i,j} x_{ij}^* r_{ijk} - \sum_k \left(\frac{v_k}{y_k} - b_k \right) \leq 0 \quad (27)$$

$$\begin{aligned} \text{Rewriting, } Z(LR_{\underline{Y}}) &= \underset{X}{\text{Min}} \sum_{i,j} x_{ij} \left[a_{ij} + \sum_k r_{ijk} \left(b_k + \left(\frac{v_k}{y_k} - b_k \right) \right) \right] \\ &\quad - \sum_k \left(\frac{v_k}{y_k} - b_k \right) \end{aligned}$$

subject to (2) and (6a)

$$\begin{aligned} &= \underset{X}{\text{Min}} \left\{ \sum_{i,j} x_{ij} \left(a_{ij} + \sum_k r_{ijk} b_k \right) \right. \\ &\quad \left. + \sum_k \left(\frac{v_k}{y_k} - b_k \right) \sum_{i,j} x_{ij} r_{ijk} - \sum_k \left(\frac{v_k}{y_k} - b_k \right) \right\} \end{aligned}$$

subject to (2) and (6a)

$$\begin{aligned} &= \sum_{i,j} x_{ij}^* \left(a_{ij} + \sum_k r_{ijk} b_k \right) \\ &\quad + \sum_k \left(\frac{v_k}{y_k} - b_k \right) \sum_{i,j} x_{ij}^* r_{ijk} - \sum_k \left(\frac{v_k}{y_k} - b_k \right) \\ &\leq \sum_{i,j} x_{ij}^* \left(a_{ij} + \sum_k r_{ijk} b_k \right) = Z(LR_b) \end{aligned}$$

by (27), or $Z(LR_v) \leq Z(LR_b)$; it follows that $v = b$ solves problem (D).

2.3 Relaxation (PR_ℓ)

Theorems 1 and 3 are useful in providing a choice of Lagrange multipliers as a starting point in solving a relaxation of problem (P) at the root node. Theorem 2, similar to Theorem 1, provides results for a partial solution of problem (P), i.e., at a node other than the root node where some of the x_{ij} and y_k have been fixed at 1 or 0.

Theorem 1 is important in pointing out that a certain set of Lagrange multipliers v such that $v_k \geq b_k$ for all k would provide an optimal choice. Theorem 3 narrows this choice to $v_k = b_k$ for all k for a specific situation, i.e., when the resulting solution is feasible for problem (P).

Letting $v_k = b_k$ for all k , problem (LR_v) becomes:

$$(LR_b) \left\{ \begin{array}{ll} \text{Minimize} & \sum_i \sum_j c_{ij} x_{ij} \\ \text{subject to} & \sum_i x_{ij} = 1 \quad \forall j \\ & x_{ij} = 0 \text{ or } 1 \quad \forall i, j \end{array} \right. \quad (28)$$
$$(2)$$
$$(6a)$$

$$\text{where } c_{ij} = a_{ij} + \sum_k b_k r_{ijk}. \quad (29)$$

Note that problem (LR_b) is very easy to solve; its optimal value is just the sum of the minimum (over i) c_{ij} for all j , i.e.,

$$Z(LR_b) = \sum_j \min_i \{c_{ij}\} \quad (30)$$

We solve this problem as a starting point at the root node in our branch-and-bound procedure.

As we move to other nodes by fixing some of the variables, we must deal with problems having the form of problem (P_ℓ) instead of problem (P) . The appropriate relaxation is then problem $(LR_{\ell,v})$, whose optimal value $Z(LR_{\ell,v})$ is the lower bound required at node ℓ . Our algorithm branches only on x_{ij} variables and uses the constraints (5') to fix appropriate y_k variables at values of 1. More precisely, if x_{ij} is fixed at 1 and $e_{ik} = 1$, then y_k must be 1 in every feasible completion of problem (P) so we can include the index k in T and fix y_k at 1. To account for the various possible combinations of i and j , we define

$$\begin{aligned}\alpha_{k\ell} &= 1 \text{ if } x_{ij} e_{ik} > 0 \text{ for any } (i,j) \in S, \\ &= 0 \text{ otherwise.}\end{aligned}\tag{31}$$

At any node ℓ then, y_k is fixed at 1 and $k \in T$ if $\alpha_{k\ell} = 1$.

There is another way in which it is appropriate to fix y_k at 1 at node ℓ . If the available choice of designs for some activity j requires the use of facility k , then y_k may be set to 1. Formally, define

$$W = \{j | (i,j) \in S \text{ and } x_{ij} = 1 \text{ for some } i\}\tag{32}$$

and its complement \bar{W} . Then define

$$\begin{aligned}\beta_{k\ell} &= 1 \text{ if } \sum_{\substack{j \in \bar{W} \\ (i,j) \in S}} \min_i d_{ijk} > 0, \\ &= 0 \text{ otherwise.}\end{aligned}\tag{33}$$

Then y_k is fixed at 1 and $k \in T$ if $\beta_{k\ell} = 1$. It is convenient to combine these two notations in forcing y_k to 1. Define

$$\delta_{kl} = \max \{ \alpha_{kl}, \beta_{kl} \} \quad (34)$$

so y_k is fixed at 1 and $k \in T$ if $\delta_{kl} = 1$.

To return to the relaxation problem $(LR_{\bar{\lambda}, \bar{v}})$, we must make a choice of the vector v of Lagrange multipliers. Of course, we would like to use an optimal choice, i.e., a vector v that solves problem $(D_{\bar{\lambda}})$.

Recall, however, that Theorem 2 did not provide us any useful information about the optimal value of v_k if $k \in T$ and $y_k = 1$. To simplify our approach and have recourse to the results of Theorems 1 and 3, we choose $v_k = 0$ if $k \in T$ and $y_k = 1$. Note that there are no $k \in T$ such that $y_k = 0$ because of practical considerations and because our branching rule only results in fixing y_k values at 1. Problem $(LR_{\bar{\lambda}, \bar{v}})$ now takes the form

$$(LR_{\bar{\lambda}, \bar{v}}) \left\{ \begin{array}{l} \text{Minimize} \quad \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_{k \in \bar{T}} v_k r_{ijk} \right) - \sum_{k \in \bar{T}} y_k \left(v_k - b_k \right) + \sum_{k \in T} b_k \\ \text{subject to} \quad \sum_i x_{ij} = 1, \quad \forall j \\ x_{ij}, y_k = 0 \text{ or } 1 \text{ for all } (i, j) \in \bar{S}, k \in T. \end{array} \right. \quad (35)$$

Note that in this problem $(LR_{\bar{\lambda}, \bar{v}})$, $\bar{v}_k = 0$ if $k \in T$. Also note how closely it resembles problem (LR_v) , the relaxation at the root node. As in that case, we would like the lower bound $Z(LR_{\bar{\lambda}, \bar{v}})$ to be as large as possible, i.e., we seek \bar{v} to

$$(D_{\bar{\lambda}}) \left\{ \begin{array}{l} \text{Maximize} \quad [Z(LR_{\bar{\lambda}, \bar{v}})] \\ \bar{v} \geq 0 \end{array} \right. \quad (36)$$

Because of the close similarity of problems $(LR_{\bar{\lambda}, \bar{v}})$ and (LR_v) , it is possible to obtain results about problem $(D_{\bar{\lambda}})$ that are analogous to those obtained about problem (D) . We state these results as Theorems 4 and 5. Their proofs are omitted because they follow precisely the

proofs of Theorems 1 and 3, respectively, and their validity follows from the fact that problem $(LR_{\ell, \bar{v}})$ is essentially the same as problem (LR_v) but involves only the free variables.

Theorem 4: There exists an optimal solution to problem (D_{ℓ}) in which $v_k \geq b_k$ for all $k \in \bar{T}$.

Theorem 5: Let (X^*, Y^*) solve problem $(LR_{\ell, \bar{v}})$ for $v_k = b_k$ for all $k \in \bar{T}$. If (X^*, Y^*) satisfies (5') for all $k \in \bar{T}$, there exists an optimal solution to problem (D_{ℓ}) in which $v_k = b_k$ for all $k \in \bar{T}$.

Just as Theorems 1 and 3 motivated us to use the relaxation problem (LR_b) to obtain our lower bound at node 1, Theorems 4 and 5 motivate us to set $v_k = b_k$ for all $k \in \bar{T}$ in relaxation problem $(LR_{\ell, \bar{v}})$ to obtain our lower bound at node ℓ . With this specification, problem $(LR_{\ell, \bar{v}})$ becomes

$$(PR_{\ell}) \left\{ \begin{array}{ll} \text{Minimize} & \sum_{i,j} c_{ij\ell} x_{ij} + FC_{\ell} \\ \text{subject to} & \sum_i x_{ij} = 1 \quad \forall j \\ & x_{ij} = 0 \text{ or } 1 \quad \forall (i,j) \in \bar{S}, \end{array} \right. \begin{array}{l} (37) \\ (2) \\ (23a) \end{array}$$

where

$$\begin{aligned} c_{ij\ell} &= a_{ij} + \sum_{k \in \bar{T}} b_k r_{ijk} \\ &= a_{ij} + \sum_{k=1}^p b_k (1 - \delta_{kl}) r_{ijk} \end{aligned} \quad (38)$$

and the fixed cost FC_{ℓ} is given by

$$FC_{\ell} = \sum_{k \in \bar{T}} b_k = \sum_{k=1}^p \delta_{kl} b_k. \quad (39)$$

This specific relaxation, problem (PR_{ℓ}) , is of the same form as problem (LR_{ℓ}) and is equally easy to solve in one pass. Its optimal value $Z(PR_{\ell})$ serves as the lower bound at node ℓ . Note that for $\ell=1$, problem (PR_{ℓ}) is the same as problem (LR_b) .

It is clear that setting each Lagrange multiplier v_k to b_k for $k \in \bar{T}$ and to 0 for $k \in T$ is not generally optimal in terms of achieving the tightest lower bound (except as per Theorem 3). But it provides a good starting point in seeking an optimal vector v and it provides an easily calculated lower bound at each node of our branch-and-bound procedure. The question of how to improve upon this choice of multiplier values will be discussed in Chapter 6.

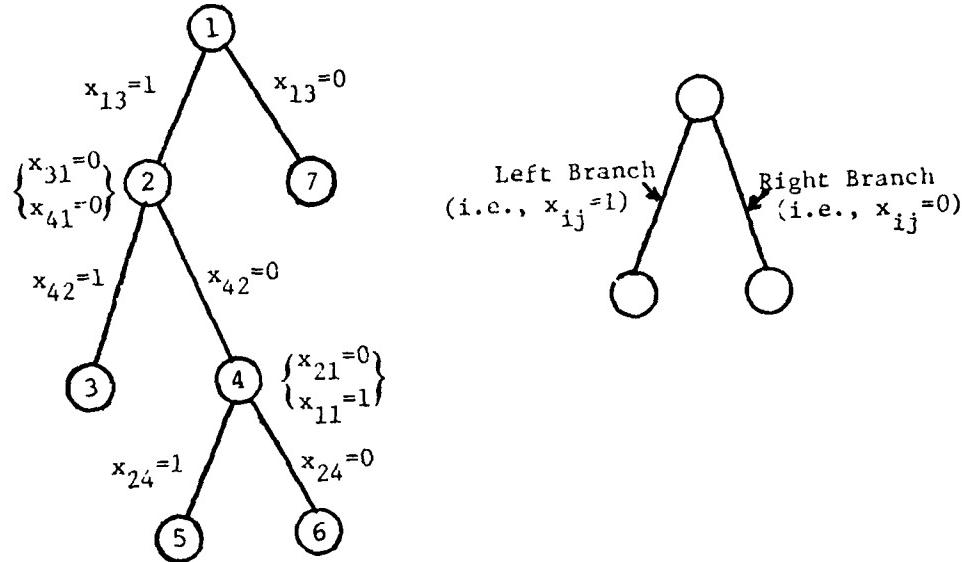
3. METHODOLOGY FRAMEWORK

The branch-and-bound procedure/methodology developed to solve problem (P) uses Lagrangian relaxation (PR_{λ}) as a basic step. The branching rule dictates which x_{ij} variable to branch on at each node. In addition, there are certain rules (e.g., the capacity rule and the bounding rule) which contribute, significantly, in improving the overall efficiency of the procedure.

Some basic terms such as fixed and free variables, partial solution and its completion were introduced in the previous chapter. This chapter first provides a preliminary discussion of the branch-and-bound methodology, [Geoffrion (1967), and Geoffrion and Marsten (1972)]. Representation and storage of the x_{ij} variables for branching and backtracking is described in order to provide continuity and consistency with the computer program covered in Chapter 4. This is followed by a description of the major components of the branch-and-bound methodology.

Branching and backtracking is done on the x_{ij} variables. The branching commences by fixing the x_{ij} variable (selected by the branching rule) to 1 and moving to the left branch node. When backtracking, we fix the corresponding x_{ij} variable at 0 and move to the right branch node (if the right branch node has not already been explored). An x_{ij} variable can also be fixed at 0 or 1 by rules other than the branching rule. The capacity rule and the bounding rule are two such rules employed in our methodology.

Figure 4a shows a branch-and-bound tree. The x_{ij} variables fixed at 0 or 1 at any node due to rules other than the branching rule are shown in parenthesis at the appropriate node.



Node 1 is the root node and also the parent node for nodes
 Node 2 and 7
 Node 2 is the parent node for nodes 3 and 4, etc.

Figure 4a.
 A branch-and-bound tree illustration

<u>Node (ℓ)</u>	<u>Partial Solution (S_ℓ)</u>
1	\emptyset
2	{103, -301, -401}
3	{103, -301, -401, 402}
4	{103, -301, -401, -402, -201, <u>101</u> }
5	{103, -301, -401, -402, -201, <u>101</u> , 204}
6	{103, -301, -401, .. 402, -201, <u>101</u> , -204}
7	{-103}

Figure 4b.
 Partial solutions for the above illustration (Figure 4a)

For problem (PR_λ) , a partial solution corresponding to set S at node $λ$, i.e., $S_λ$ contains x_{ij} variables assigned values of 1 or 0 . For simplicity in the computer program, an x_{ij} variable fixed at 1 is represented as $(100 i + j)$, whereas an x_{ij} variable fixed at 0 as $-(100 i + j)$, e.g., $x_{32} = 1$ and $x_{32} = 0$ are represented as 302 and - 302 respectively. Since branching is done on x_{ij} variables, it is necessary to make a distinction between x_{ij} variables fixed at 1 due to the branching rule and those fixed at 1 due to the other rules. We make this distinction by underlining the positive number to represent an x_{ij} fixed at 1 due to the other rules. For example, 204, - 301, 103 represent, respectively, $x_{24} = 1$ due to the branching rule, $x_{31} = 0$ due to the branching rule or any other rule, and $x_{13} = 1$ due to a rule other than the branching rule.

Figure 4b shows the partial solutions $S_λ$ of the branch-and-bound tree in Figure 4a.

Implicit enumeration involves generating a sequence of partial solutions and simultaneously considering all completions of each. For our minimization problem, we start with an initial solution having a very large value (infinity) as an initial upper bound. As the computations proceed, feasible solutions (those satisfying the capacity constraints) are discovered from time to time, and the best one yet found is retained as an incumbent solution with the corresponding value as the best upper bound. It may happen that for a given partial solution $S_λ$ we can determine a best completion of $S_λ$, i.e., a feasible completion that minimizes the objective function value among all feasible completions of $S_λ$. If such a best feasible completion is better than the best upper bound, then it replaces the latter. Or we may be able to determine that $S_λ$ has no feasible completion better than the incumbent. In either case, we can fathom $S_λ$. (Various situations of fathoming and back-

tracking in our branch-and-bound procedure are described in the following discussion.) All completions of a fathomed partial solution S_ℓ have been implicitly enumerated in the sense that they can be excluded from further consideration (with the exception of the relevant best feasible solution of S_ℓ if it has been retained as the best upper bound).

In our branch-and-bound procedure, at any given node where we can fathom S_ℓ , we backtrack to the parent node and move to the right-hand branch (if that branch has not already been explored) by fixing the appropriate x_{ij} variable at 0. However, if the right-hand branch has already been explored, we continue backtracking to a parent node where we can move to a right-hand branch. For example, in Figure 4a, when backtracking from node 3, we move to the parent node 2, and to the right to node 4 by setting $x_{42} = 0$. However, when backtracking from node 6, we move back to node 4, then back to node 2, then back to node 1, and to the right to node 7 by setting $x_{13} = 0$.

On the other hand, if the partial solution S_ℓ cannot be fathomed, we branch to the left and augment S_ℓ by fixing a free variable x_{ij} at 1 (based on the branching rule), and then we try to fathom the resulting partial solution. In addition to the one variable selected by the branching rule, some other free x_{ij} variables can also be fixed at 0 or 1 according to the application of rules other than the branching rule. Note that this can also happen when backtracking, i.e., when S_ℓ has been fathomed and we backtrack and move to the right by setting the appropriate x_{ij} variable to 0.

Let us consider examples of both situations, i.e., when S_ℓ has not been fathomed and when S_ℓ has been fathomed. In Figure 4a we cannot fathom S_1 (i.e., S at node 1), so we move to node 2 by

augmenting S_1 by fixing $x_{13} = 1$ based on the branching rule, and by fixing $x_{31} = 0$ and $x_{41} = 0$ based on the application of the other rules. Similarly, we move from node 2 to node 3 by augmenting S_2 by fixing $x_{42} = 1$. As an example of backtracking, when we fathom S_3 , we move back to the parent node 2, and to the right to node 4, getting a new partial solution S_4 by replacing $x_{42} = 1$ with $x_{42} = 0$, and further augmenting it by fixing $x_{21} = 0$ and $x_{11} = 1$ based on the application of the other rules.

Computationally, the storage and update of partial solution S_ℓ is easily accomplished by considering Figure 4b. If, at a given node, the partial solution S_ℓ has not been fathomed, e.g., at node 4, determine the next branching variable by using the branching rule, i.e., x_{24} , and augment S_4 by adding 204 as the last entry. Also, augment S_4 with any other free x_{ij} variables, if appropriate, depending on the application of the other rules. Now, consider the case where the partial solution S_ℓ has been fathomed, e.g., at node 6, and we backtrack; starting with the last entry in S_ℓ . we consider one entry at a time, going backwards, until we find a positive number which is not underlined. In our example, it is 103. In other words, we must branch to the right by fixing $x_{13} = 0$, i.e., we replace 103 with - 103 and we are at node 7. Should we find that we have no positive number, the procedure terminates since we are back at the root node and the right branch has already been explored. This happens when backtracking from node 7.

In the branch-and-bound procedure we generate a sequence of partial solutions as we move from one node to another. This sequence is non-redundant in the sense that no completion of a partial solution ever duplicates a completion of a previous partial solution that has been fathomed.

Since one of the x_{ij} values, for each j , must be 1, a total of $(2m-1)^n$ nodes are theoretically possible for complete enumeration. However, most of the solutions may be infeasible because of the capacity constraints. The branch-and-bound procedure, through a judicious choice of branching variables, and elimination of certain infeasible and non-optimal assignments through various rules, turns out to be a practical and computationally efficient algorithm. The various components of this procedure are described next. Detailed procedural steps and the solution of a test problem will be covered in Chapter 4.

3.1 Bounds

3.1.1 Lower Bound

At a given node ℓ in the branch-and-bound tree, a lower bound (LOWB) is obtained by solving relaxed problem (PR_ℓ) .

$$\text{LOWB} = Z(PR_\ell) \quad (40)$$

Recall that problem (PR_ℓ) is very easy to solve by considering the minimum $c_{ij\ell}$ over those j 's for which x_{ij} is not fixed at 1, i.e., $j \in \bar{W}$, where \bar{W} is the complement of W defined by expression (32).

$$Z(PR_\ell) = \sum_{j \in W} c_{ij\ell} + \sum_{j \in \bar{W}} \min_i c_{ij\ell} + FC_\ell, \quad (41)$$

where $c_{ij\ell}$ is given by expression (38), i.e.,

$$c_{ij\ell} = a_{ij} + \sum_k b_k (1 - \delta_{k\ell}) r_{ijk}, \quad (38)$$

and the fixed cost (FC_ℓ) is given by expression (39), i.e.,

$$FC_\ell = \sum_k \delta_{k\ell} b_k, \quad (39)$$

where $\delta_{k\ell}$ is given by expression (34).

Note that if none of the x_{ij} variables is fixed at 1, as is generally the case at the root node, then all $\delta_{kl} = 0$, and, therefore, $FC_1 = 0$, and $c_{ijl} = a_{ij} + \sum_{k=1}^p b_k r_{ijk}$. $Z(PR_1)$ is, then, simply the middle part of expression (41). We use the term "generally" because it is possible that the capacity rule could force certain x_{ij} variables to 1 (or 0) at the root node, prior to solving the relaxed problem (PR_1) .

3.1.2 Upper Bound

At any given node χ , let $X = \{x_{ij}\}$ represent the solution of problem (PR_χ) . If this solution is feasible for problem (P), i.e., if X satisfies the capacity constraints (5) or (5')

$$\sum_{\substack{i \\ x_{ij} \in X}} \sum_j d_{ijk} x_{ij} \leq s_k y_k \quad \forall k, \quad (42)$$

where $y_k = 1$ if $\sum_{\substack{i \\ x_{ij} \in X}} \sum_j d_{ijk} x_{ij} > 0$,

$$= 0 \text{ otherwise ,} \quad (43)$$

then the value of problem (P) corresponding to this solution gives an upper bound (UPB):

$$UPB = \sum_{\substack{i \\ x_{ij} \in X}} \sum_j a_{ij} x_{ij} + \sum_k b_k y_k, \quad (44)$$

where y_k is defined by (43).

3.1.3 Best Upper Bound

A current lowest upper bound is retained as the best upper bound (BUB), the corresponding solution X representing the incumbent solution.

The branch-and-bound procedure is initiated by assuming a very large value as the best upper bound, and is replaced by better (lower) values as the procedure continues.

A positive fractional value ϵ can be specified if a sub-optimal solution is acceptable. For example, for $\epsilon = 0.001$, the resulting solution value is guaranteed to be within 0.1 percent of the optimal solution value. When ϵ is non-zero, the adjusted best upper bound (BUBS) is defined as:

$$\text{BUBS} = \text{BUB}/(1 + \epsilon). \quad (45)$$

Obviously when $\epsilon = 0$, $\text{BUBS} = \text{BUB}$.

3.2 Facility Usage Rule

This rule is used to identify facilities forced into usage at a given node ℓ and hence fix corresponding free variables y_k at 1.

For a partial solution S_ℓ , define

$$\begin{aligned}\bar{d}_{jkl} &= d_{ijk} \quad \text{if } j \in W, \\ &= \min_i d_{ijk} \quad \text{if } j \in \bar{W}, \\ &\quad (i,j) \in \bar{S}\end{aligned} \quad (46)$$

The facility usage rule states that for any facility k , where y_k is not already fixed at 1, if $\sum_j \bar{d}_{jkl} > 0$, then facility k is forced into usage and, therefore, y_k should be fixed at 1.

This rule is applied at every node prior to applying the capacity rule. In other words, this rule is applicable to capacitated as well as uncapacitated problems.

3.3 Capacity Rule

This rule is designed to "exclude" infeasible assignments prior to solving the relaxed problem (PR_ℓ). This is done by exploiting the

relationship between the capacities required (d_{ijk}) and the capacities available (s_k) for a given partial solution of problem (P).

The capacity rule states that for a facility k and an activity j , "exclude" a free x_{ij} variable (i.e., fix it at 0) for which

$$(d_{ijk} - \bar{d}_{jkl}) > (s_k - \sum_j \bar{d}_{jkl}), \quad (i,j) \in \bar{S} \quad (47)$$

where \bar{d}_{jkl} is defined by expression (46). The right-hand side of this inequality (47), when positive, represents the available capacity at facility k . The left-hand side shows, for a given j , the difference between a d_{ijk} corresponding to a free x_{ij} variable and \bar{d}_{jkl} . If, for a specific d_{ijk} , this difference is more than the available capacity, the corresponding free x_{ij} variable, if fixed at 1, would result in an infeasible solution. Thus, by looking ahead, we can exclude such a free x_{ij} variable by assigning it a value of 0.

Note that if the right-hand side of expression (47) is negative, then any completion of such a partial solution will be infeasible and we backtrack in our branch-and-bound procedure.

The capacity rule is applied to all the facilities by considering one facility at a time. The cycle of examining all the facilities continues until no more assignments can be excluded. During the course of application of this rule, if all but one of the free x_{ij} variables have been excluded (fixed at 0) for a given j , then that particular x_{ij} variable is fixed at 1 because of constraints (2), i.e., each activity j must be assigned to one and only one design i . The partial solution is updated accordingly to reflect the x_{ij} variables fixed at 0 or 1 due to the application of the capacity rule.

The capacity constraints for an uncapacitated problem are not active. Hence, the capacity rule is useful only for capacitated problems.

3.4 Branching Rule

This rule provides the choice of the x_{ij} variables on which to branch. If the partial solution at a given node ℓ is not fathomed, we branch further by fixing a free x_{ij} variable at 1 and moving to the left branch node.

According to the branching rule the choice of the branching variable depends on the $c_{ij\ell}$ values and is such that the corresponding x_{ij} , if perturbed, has the maximum impact on the optimal value of problem (PR_ℓ) .

For a given j , define $c_{i_1 j \ell}$, the minimum permissible $c_{ij\ell}$, and $c_{i_2 j \ell}$, the second smallest permissible $c_{ij\ell}$, i.e.,

$$c_{i_1 j \ell} = \min_i c_{ij\ell} \text{ for } j \in \bar{W} \text{ and } (i,j) \in \bar{S} \quad (48)$$

$$\text{and } c_{i_2 j \ell} = \min_{\substack{i \\ i \neq i_1}} c_{ij\ell} \text{ for } j \in \bar{W} \text{ and } (i,j) \in \bar{S} \quad (49)$$

$$\text{For each } j \in \bar{W}, \text{ define } D_{j\ell} = c_{i_2 j \ell} - c_{i_1 j \ell}. \quad (50)$$

Our branching rule states that a free x_{ij} variable corresponding to $c_{i_1 j \ell}$ such that $D_{j\ell}$ is maximized over all j , is selected as the next branching variable and assigned a value of 1.

3.5 Bounding Rule

This rule is designed to "exclude" certain non-optimal assignments. These assignments cannot lead to an optimal solution as we branch from one node to the next left branch node.

The bounding rule states that a free x_{ij} variable should be excluded (by assigning it the value 0) for which

$$(c_{ij\ell} - c_{i_1 j \ell}) > (BUBS - LOWB) \quad \text{for } j \in \bar{W} \quad \text{and } (i, j) \in \bar{S} \quad (51)$$

where $c_{i_1 j \ell}$, BUBS, and LOWB are given by expressions (48), (45), and (40), respectively.

Thus, by looking ahead, we exclude those assignments which will provide lower bounds higher than BUBS.

The bounding rule is applied to each $j \in \bar{W}$ just prior to selecting the x_{ij} variable for branching to the left.

As in the case of the capacity rule, if the bounding rule results in excluding (fixing at 0) all but one of the free x_{ij} variables for a given $j \in \bar{W}$, then that particular x_{ij} variable is fixed at 1. Also the partial solution is updated accordingly to reflect the x_{ij} variables fixed at 0 or 1 due to the application of the bounding rule.

3.6 Backtracking Rules

If a partial solution at a given node has been fathomed, we backtrack. The backtracking rules are typical of a branch-and-bound procedure. In addition, the application of the capacity rule and the bounding rule can lead to backtracking. The criteria for backtracking include the following.

- (a) When applying the capacity rule, if the available capacity given by the right-hand side of inequality (47) is negative, i.e., $(s_k - \sum_j \bar{d}_{jk\ell}) < 0$, then backtrack.
- (b) If $LOWB \geq BUBS$, then backtrack. Otherwise compute UPB if the solution is feasible in problem (P). Then update BUB and BUBS if $UPB < BUB$; and backtrack if $LOWB = BUBS$.
- (c) If further branching is not possible, then backtrack. This can happen due to the capacity rule, the bounding rule, or the branching rule if the updated partial solution is such that no further branching is possible, i.e., x_{ij} variables are fixed at 1 for all j , or equivalently, $\bar{W} = \emptyset$.

When any of the backtracking criteria apply, we backtrack to the parent node and move to the right branch node (if the right branch has not already been explored) by fixing the appropriate x_{ij} variable at 0 . If the right branch has already been explored, we continue backtracking to a parent node where we can move to a right branch node. The branch-and-bound procedure terminates when we backtrack to the root node and find that the right branch node has already been explored.

4. COMPUTATIONAL STEPS AND THE COMPUTER PROGRAM

A computer program called ZIPCAP (an acronym for Zero-one Integer Program for multiactivity multifacility Capacity-constrained Assignment Problems) implementing the branch-and-bound methodology has been developed.

Detailed procedural steps and guidelines to use the computer program are described in a separate document [Chhabra and Soland (1980)] titled "Program Description and User's Guide for ZIPCAP--a Zero-one Integer Program to solve multiactivity multifacility Capacity-constrained Assignment Problems." Specifically, the document includes:

- Problem formulation (P) and potential areas of application
- Overall flow diagram and detailed procedural steps for the computer program
- Program listing and dictionary of the symbolic names. The listing includes extensive use of comment cards to explain various computational steps.
- User information including
 - schematic diagram of the deck structure,
 - detailed instructions for the job control (JCL) cards, program parameter card, program options card, and the various other input data cards.
- Three test problems to demonstrate the use of the program. The display includes coded input and annotated outputs reflecting the use of selected program options.

As mentioned earlier, ZIPCAP is primarily designed for capacitated problems. However, uncapacitated problems can be solved as a special case, and this is demonstrated by including an uncapacitated test problem.

Because of the extensive coverage of the program description and user guidelines in the above document, this chapter provides only an overview of the computer program, including an overall flow diagram, and a summary of the program options, in order to provide continuity in this document. In addition, a step-by-step description of a test problem is presented to demonstrate the use of the various components of the branch-and-bound methodology. The computer printout showing step-by-step details is obtained by use of one of the program options. The use of this option to display detailed steps in this document, in fact, complements the use of the various options demonstrated in the other document.

4.1 The Program

Figure 5 presents a simplified flow diagram of the branch-and-bound procedure. The major computational steps for the computer program are numbered in circles. These steps are essentially based on the methodology components described in the previous chapter. A step-by-step description has been included in the other document [Chhabra and Soland (1980)].

The computer program ZIPCAP is written in FORTRAN IV, and has been developed and tested on an IBM 3031 at the George Washington University. The program, comprising about 480 lines is currently dimensioned for a maximum problem size of 35 designs (m), 35 activities (n) and 30 facilities (p). The program size to execute a problem has two components: one, due to the program itself, comprising 173 K bytes, and the other dependent on the dimensions of the arrays given by the following functional relationship.

$$f(m, n, p) = 4[(p+4)mn + (m+5)p+9n] \text{ bytes}$$

The computer program listed in the other document has since been further improved. The basic improvement has been the addition of the facility usage rule. This rule, as described in Chapter 3, is applied both to capacitated and uncapacitated problems just before the application of the capacity rule. For completeness of this document, a revised program listing is included in Appendix A. It may be mentioned that

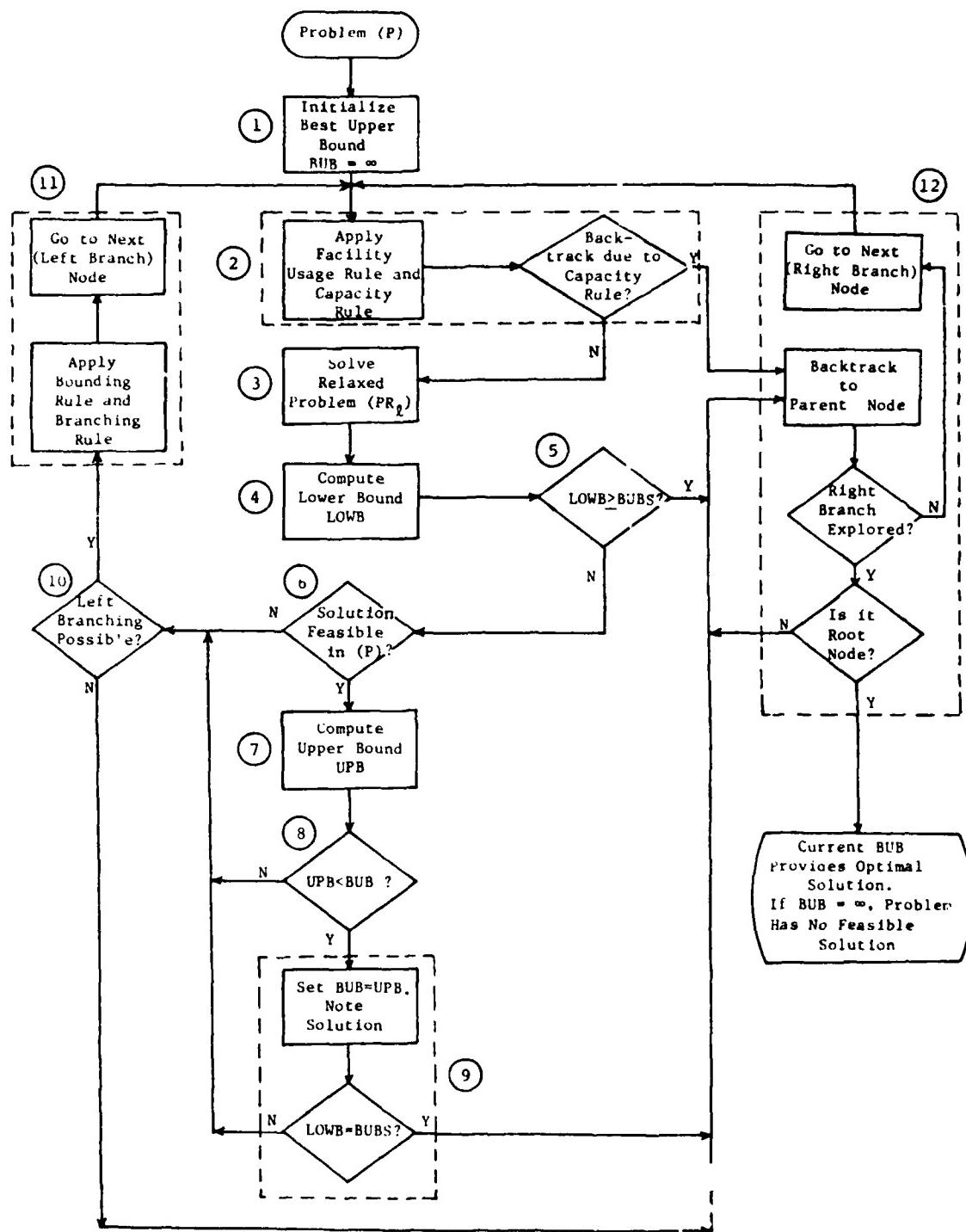


Figure 5.
Simplified flow diagram for the branch-and-bound procedure

the revised program solves the test problems included in the other document more efficiently -- in less time and in fewer nodes (with an average reduction in nodes of 31 percent). The improvement in efficiency seems to result from the "multiplicative" effect of the various rules. Another improvement made is that the computer printout always displays the node number (IBNOD) at which the best upper bound changes (improves) and the corresponding values of the best upper bound (BUB) and the adjusted best upper bound (BLBS).

ZIPCAP provides numerous options to the program user. These options, described in the other document, are summarized in Table 3.

Option ICAPR, the capacity rule, is automatically skipped by the program when solving an uncapacitated problem. Option ISTEP, the intermediate steps' listing, even when skipped, provides information on the total number of nodes explored. A summary listing provides necessary information to construct the branch-and-bound tree, whereas a detailed listing of the intermediate steps is useful when changing or debugging the program.

Option EPS, the optimal/suboptimal solution, provides the flexibility of obtaining a suboptimal value guaranteed to be within a specified fraction of the optimal value. The resulting solution may be suboptimal but could provide a considerable saving in terms of exploring fewer nodes in comparison to those necessary for obtaining an optimal solution.

Option ET, by providing important information at a specified elapsed time, is useful in a situation where the total time allocated to solve a problem may not be sufficient and the program terminates before verifying an optimal solution. The information provided by this option includes an updated partial solution showing the x_{ij} variables fixed at 0 or 1, at the current node being explored at the specified time ET. By looking at the first few variables displayed in the partial solution of the current node, it is possible to assess the extent of the branch-and-bound tree explored until time ET. For

Table 3

SUMMARY OF ZIPCAP OPTIONS

<u>Option Name</u>		<u>Alternatives Available to User</u>
1. IINPT	-- Input Listing	<ul style="list-style-type: none">• List input data• Skip this option
2. ICAPR	-- Capacity Rule	<ul style="list-style-type: none">• Use capacity rule• Skip this option
3. ISTEP	-- Intermediate Steps Listing	<ul style="list-style-type: none">• Skip listing of intermediate steps• Provide a summary of intermediate steps• Provide detailed intermediate steps
4. IUNCAP	-- Capacitated/Uncapacitated Problem	<ul style="list-style-type: none">• Solve a capacitated problem• Solve an uncapacitated problem
5. EPS	-- Optimal/Suboptimal Solution	<ul style="list-style-type: none">• Optimal solution• Suboptimal solution acceptable within a specified fractional value (epsilon)
6. ET	-- Information at a specified Elapsed Time	<ul style="list-style-type: none">• Provide the following information at elapsed time ET:<ul style="list-style-type: none">- Best upper bound, corresponding solution, and the node at which found- node being explored and detailed steps for that node• Skip this option

example, in view of the terminology in Figure 4b (Chapter 3), if, at an arbitrary node, the first term of the partial solution is positive, i.e., the x_{ij} variable has value 1, then we are still in the left half of the total branch-and-bound tree. If the first term is negative, i.e., the x_{ij} variable has value 0, then we are in the right half of the total branch-and-bound tree and have explored half of the total (theoretical) solutions corresponding to the left half of the tree. If the first two terms are negative, i.e., the first two x_{ij} variables have value 0, then one quarter of the total (theoretical) solutions remain to be explored, since we are in the next right half of the right half of the total branch-and-bound tree, as illustrated in Figure 6.

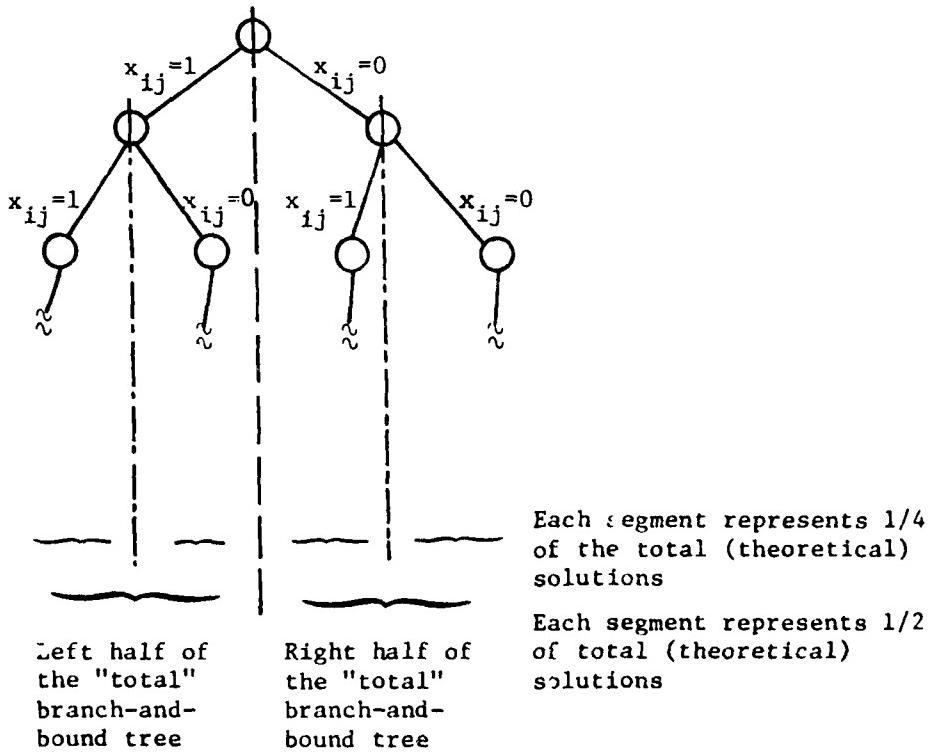


Figure 6
Illustration for estimating the extent of the branch-and-bound tree explored

Recall from Chapter 3, that a total of $(2m-1)^n$ nodes are theoretically possible. Thus, if the first g [$g \leq (m-1)n$] terms at an arbitrary node are negative, then theoretically about $[(2m-1)^n / 2^g]$ nodes remain to be explored.

4.2 An Illustrative Example

We consider a capacitated test problem with five designs (m), four activities (n), and eight facilities (p) to demonstrate the use of the branch-and-bound procedure and the computer program.

The computer printout for this problem showing step-by-step details for a couple of nodes is presented in Appendix B.

As shown in the beginning of the printout, the options selected are:

- . IINPT = 1, i.e., list the input data
- . ICAPR = 1, i.e., use the capacity rule
- . ISTEP = 2, i.e., list detailed intermediate steps
- . IUNCAP = 1, since this is a capacitated problem
- . EPS = 0.0 implying that an optimal solution is desired
- . ET = 0.0 since a detailed listing of intermediate steps will be available.

Following the listing of the options, input data listed for the problem include variable costs a_{ij} , fixed costs b_k , available capacities s_k , and capacities required d_{ijk} . The e_{ik} values are generated by the computer program.

The computer program follows the procedural steps marked in the flow diagram presented in Figure 5. These steps, along with the relevant terminology used in the computer printout, are described below for a couple of nodes, followed by a complete branch-and-bound tree for this problem. As mentioned earlier, a dictionary of the symbolic names used in the computer program is included in the other document.

Node 1

Step 1: Initialize.

Initialize BUB = 9999999.0, and since EPS = 0.0, BUBS = BUB.
Also S = \emptyset and W = \emptyset . In the computer printout, vector
FIX(J) represents the set W, and matrix CX(I,J) represents both, fixed
and free x_{ij} variables. In the CX(I,J) matrix, an x_{ij} variable fixed
at 1 or 0 is represented as 1 or 2, respectively, and a free x_{ij} variable
is represented by the value 0. Initially, all the x_{ij} variables are free
as shown by matrix CX(I,J) in the printout.

Step 2: Apply the facility usage rule and the capacity rule for
 $k=1,2,\dots,8$.

In the printout, MIND(J) represents \bar{d}_{jkl} defined by expression (46),
and MINSD represents $\sum_j \bar{d}_{jkl}$. As shown in the printout, MINSD is 0 for
 $k=1,2,\dots,8$, and so the facility usage rule does not force any facilities
into usage; and as shown by matrix CX(I,J) for $k=1,2,\dots,8$, the capacity
rule does not fix any x_{ij} variables.

Step 3: Solve the relaxed problem (PR_1) .

In the printout FLB(K) represents δ_{kl} , given by expression (34),
for computing FC_ℓ , and C(I,J) represents c_{ijl} defined by expression
(38). Being at the root node, $\ell = 1$. Further the solution of problem
 (PR_ℓ) , i.e., $X = \{x_{ij}\}$ is shown in the printout by SOLX(J) which
for (PR_1) is $X = \{x_{41} = x_{42} = x_{23} = x_{44} = 1\}$.

Step 4: Compute the lower bound.

The expressions (40) and (41), i.e.,

$$LOWB = Z(PR_\ell) \quad (40)$$

$$= \sum_{j \in W} c_{ijl} + \sum_{\substack{j \in \bar{W} \\ (i,j) \in \bar{S}}} \min_i c_{ijl} + FC_\ell \quad (41)$$

are represented in the printout as

$$\begin{aligned} \text{LOWB} &= \text{MINSC} + \text{FC} \\ &= 729839.3125 + 0 = 729839.3125 \end{aligned}$$

Step 5: Compare LOWB with BUBS.

Since LOWB < BUBS, go to Step 6

Step 6: Check if solution X is feasible in problem (P), i.e., expression (42) is satisfied.

$$\sum_{\substack{i j \\ x_{ij} \in X}} d_{ijk} x_{ij} \leq s_k y_k \quad \forall k \quad (42)$$

In the printout, NSUMD represents the left-hand side of this inequality, and for each k , the capacity constraints are satisfied.

Step 7: Compute the upper bound.

UPB is given by expression (44), i.e.,

$$\text{UPB} = \sum_{\substack{i j \\ x_{ij} \in X}} a_{ij} x_{ij} + \sum_k b_k y_k \quad (44)$$

In the printout, the corresponding expression is represented as

$$\begin{aligned} \text{UPB} &= \text{NSUMA} + \text{FCUB} \\ &= 678,502 + 101,000 = 779502.0 . \end{aligned}$$

Step 8: Compare UPB with BUB.

Since UPB < BUB, go to Step 9.

Step 9: Set BUB = 779502.0 . Since EPS = 0.0, BURS = BUB.

Since LOWB < BUBS, go to Step 10.

Step 10: Left branching is possible since $W = \phi$ as shown by vector FIX(J); go to Step 11.

Step 11: Apply the bounding rule and the branching rule.

According to our bounding rule, a free x_{ij} variable is excluded

(fixed at 0) for which

$$(c_{ij\ell} - c_{i_1 j \ell}) > (\text{BUBS} - \text{LOWB}) \text{ for } j \in \bar{W} \text{ and } (i, j) \in \bar{S} \quad (51)$$

For x_{13} , $(210,381.4375 - 145,201.5) > (779,502.0 - 729,839.3125)$.

This also holds for x_{33} and x_{14} , i.e., the bounding rule results in fixing x_{13} , x_{33} , and x_{14} at 0. This is shown in the printout by matrix CX(I,J) where the corresponding variables have been assigned the value 2 because of the bounding rule.

The branching rule directs us to select a free x_{ij} variable corresponding to $c_{i_1 j \ell}$ for which $D_{j\ell} = c_{i_2 j \ell} - c_{i_1 j \ell}$ is maximized over all j . In the printout, $c_{i_2 j \ell}$, $c_{i_1 j \ell}$, and $D_{j\ell}$ are represented by NMINC(J), MINC(J) and DIFBR(J), respectively. Since D_{21} is the maximum, x_{42} is selected as the next left branching variable. This is shown in the printout by BR1 and is represented as $(100 i + j)$ e.g., 402.

Using the terminology employed in Figures 4a and 4b, the x_{ij} variables fixed at 0 or 1 in the partial solution S_1 will be shown as $S_1 = \{-103, -303, -104, 402\}$. In the computer printout, vector STX displays the x_{ij} variables fixed at 0 or 1. The representation of the variables is, however, somewhat different. An x_{ij} variable fixed at 0, due to any rule, is shown as $-(100 i + j) - 1,000,000$, e.g., x_{13} is shown as $\sim 1,000,103$; an x_{ij} variable fixed at 1 due to the branching rule is represented as $(100 i + j)$, e.g., x_{42} as 402; and an x_{ij} variable fixed at 1 due to a rule other than the branching rule is shown as $(100 i + j) + 1,000,000$, e.g., x_{23} is represented as 1,000,203.

In the printout, vector STX represents updated partial solution S_1 .

We now move to Node 2.

Node 2

The updated matrix CX(I,J) and vector FIX(J) are displayed in the printout.

Step 2: Apply the facility usage rule and the capacity rule for $k=1, 2, \dots, 8$.

As shown in the printout, MINSD (representing $\sum_j \bar{d}_{jkl}$) , being positive for $l=1, 2, 3, 4$, and 5 , these facilities are forced into usage. Further, for $k=4$, expression (47) holds for x_{34} and x_{54} , i.e.,

$$(180-0) > (200-30), \text{ and}$$

$$(180-0) > (200-30), \text{ respectively.}$$

As shown by matrix CX(I,J) in the printout, these two variables are excluded (fixed at 0) by the capacity rule. Since the capacity rule results in fixing at least one variable in the first cycle, another cycle is repeated as displayed in the printout. The second cycle does not fix any more variables. Vector STX is updated accordingly.

Step 3: Solve the relaxed problem (PR₂) .

δ_{k2} represented by FLB(K) , c_{ij2} represented by matrix C(I,J), and solution X represented by SOLX(J) are displayed in the printout.

Step 4: Compute LOWB.

LOWB, from the printout, is equal to 749011 4375.

Step 5: Compare LOWB with BUBS.

Since LOWB < BUBS, go to Step 6.

Step 6: Check if solution X is feasible in (P).

In the printout, for $k=4$, NSUMD = 290 > 200 , i.e., expression (42) is not satisfied, and we go to Step 10.

Step 10: As shown by vector FIX(J), left branching is possible and we go to Step 11.

Step 11: Apply the bounding rule and the branching rule.

As displayed by matrix CX(I,J) in the printout, the bounding rule results in fixing x_{21} and x_{24} at 0. Now, for $j=4$, except for x_{44} , all the x_{ij} variables are fixed at 0; therefore x_{44} is fixed at 1. This is reflected by matrix CX(I,J), and vector FIX(J). Vector STX is updated accordingly.

The branching rule selects x_{41} as the next branching variable.

This is shown in the printout by BR1, and vector STX is updated accordingly.

We now move to Node 3.

Node 3:

The updated matrix CX(I,J) and vector FIX(J) are displayed in the printout.

Step 2: Apply the facility usage rule and the capacity rule for $k=1,2,\dots,8$.

The facility usage rule forces facilities 1 to 5, and 8 into usage. For $k=4$, the capacity rule excludes x_{45} and x_{53} , i.e., fixes them at 0; and for $j=3$, all but x_{23} being fixed at 0, x_{23} is fixed at 1. This is displayed in the printout by matrix CX(I,J) and vector FIX(J). Vector STX is updated accordingly.

Although the capacity rule has fixed at least one x_{ij} variable during the initial cycle, another cycle is not necessary, as displayed by vector FIX(J) which represents set W, since we have an x_{ij} variable fixed at 1 for each of the n columns (activities).

Step 3: Solve the relaxed problem (PR₃) .

SOLX(J) displays the solution for the relaxed problem.

Step 4: Compute LOWB.

LOWB, shown in the printout, is equal to 779502.0 .

Step 5: Compare LOWB with BUBS.

Since LOWB = BUBS, go to Step 12.

Step 12: Backtrack.

We backtrack by moving to the parent Node 2, and branching to the right by setting $x_{41} = 0$ (since the right branch has not yet been explored).

In the printout, this is accomplished by observing the last entry in vector STX, and moving backwards, one entry at a time, until we find a positive entry without 1,000,000 added to it. The corresponding x_{ij} variable is fixed at 0, and we move to the right branch node. Matrix CX(I,J), vector FIX(J) and vector STX are updated accordingly. As displayed in the printout, entry 401 in vector STX is such an entry, and variable x_{41} is fixed at 0 for branching to the right. This is shown in the printout by BRO as 401. The updated vector STX is also displayed.

We now move to Node 4.

Node 4

The updated matrix CX(I,J) and vector FIX(J) are displayed in the printout.

Step 2: Apply the facility usage rule and the capacity rule for $k=1,2,\dots,8$.

As displayed in the printout, for $k=4$, $\text{MINSD}=230 > 200$, i.e., the right-hand side of inequality (47), $(s_k - \sum_j \bar{d}_{jkl}) < 0$, and according to our backtracking rules, we backtrack, i.e., go to Step 12.

Step 12: Backtrack.

We backtrack to the parent Node 2, and since the right-hand branch has already been explored, backtrack to Node 1 and to the right-hand branch by fixing x_{42} to 0. This is shown in the printout by BRO as 402, and vector STX is updated accordingly.

We now move to the next node, i.e., Node 5.

Branch-and-Bound Tree

We continue the branch-and-bound procedure from one node to another until we backtrack to the root node and find that the right branch has already been explored. The procedure, then, terminates and the solution corresponding to the best upper bound is the optimal solution.

For this problem, a total of nine nodes are explored and the optimal value equals 779502.0. The optimal solution is $x_{41} = x_{42} = x_{23} = x_{44} = 1$ and $y_1 = y_2 = y_3 = y_4 = y_5 = y_8 = 1$. This is displayed in the computer printout on the last page of Appendix B.

Figure 7a presents the branch-and-bound tree for this problem, and shows the node numbers, the bounds, and the branching variables.

In order to demonstrate the role of the capacity rule and the bounding rule, Figure 7b displays the x_{ij} variables fixed as 0 or 1 by these rules for this test problem.

The cumulative effect of the various rules, including the facility usage rule, the capacity rule, and the bounding rule, makes the branch-and-bound procedure quite efficient. Further, the storage and updating of the x_{ij} variables fixed at 0 or 1 is done in a manner that makes utmost use of the relevant information at the preceding node.

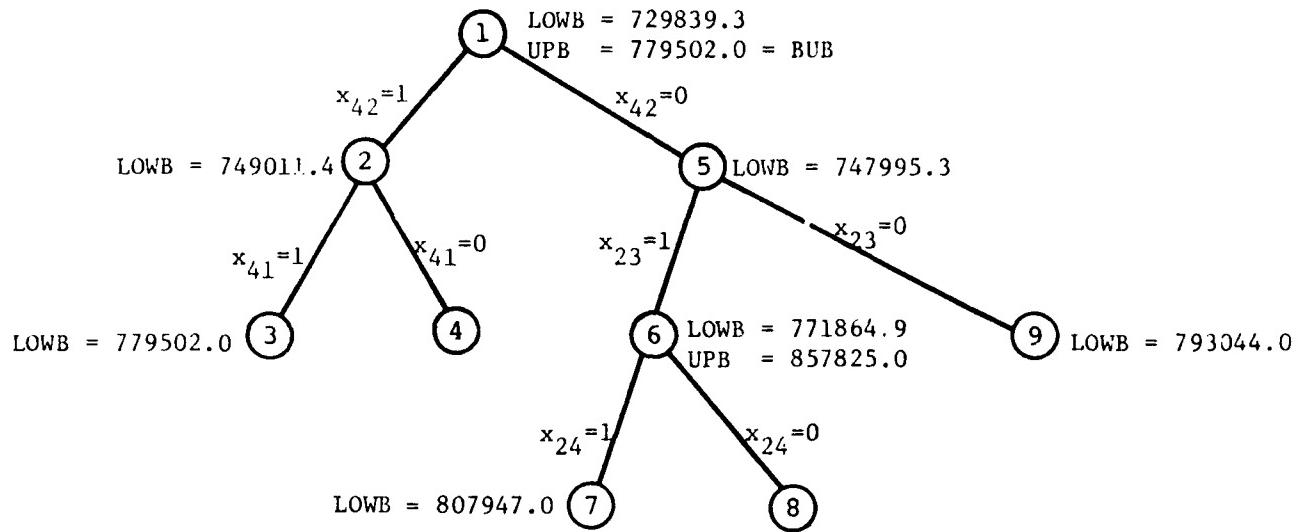


Figure 7a

Branch-and-bound tree for a test problem
(Test Problem with $m=5$, $n=4$, and $p=8$)

Node	Capacity Rule	Bounding Rule
1		$x_{13}=0, x_{33}=0, x_{14}=0$
2	$x_{34}=0, x_{54}=0$	$x_{21}=0, x_{24}=0, x_{44}=1$
3	$x_{43}=0, x_{53}=0, x_{23}=1$	
5		$x_{43}=0, x_{34}=0$
6		$x_{11}=0, x_{21}=0, x_{31}=0, x_{22}=0, x_{54}=0$
8	$x_{44}=1$	
9	$x_{53}=1, x_{44}=0, x_{54}=0, x_{24}=1$	

Figure 7b

Variables fixed by the capacity rule and the bounding rule

5. COMPUTATIONAL TEST RESULTS

The computer program ZIPCAP has been tested on several problems. Although primarily designed for capacitated problems (i.e., where the capacity constraints are active), the program can also be used for solving uncapacitated problems as a special case. Since the data available for capacitated problems were limited, some uncapacitated problems were also considered for testing the program. (Most of the data were furnished by Professor Pinkus and are related to his work on multi-echelon inventory systems.)

Table 4 presents the test results of ZIPCAP. In order to verify the optimal solutions, the test problems were also solved by using the 0-1 integer programming code RIP30C [Geoffrion and Nelson (1968)].

In the table, the problem size shows the number of designs (m), activities (n), and facilities (p). This is equivalent to solving a problem having $mn+p$ variables and $n+p$ constraints. The elapsed time represents the time in seconds to solve the problem, excluding the time to read and write the input and to write the output. The total number of nodes explored by ZIPCAP for a specified set of options is also shown.

Both RIP30C and ZIPCAP were run on an IBM 3031 at The George Washington University. The last problem in the table was not run using RIP30C because of the code's capacity limitation to 90 variables and 50 constraints.

The test problem with $m=3$, $n=4$, and $p=5$ has three variations, using different values for the facility capacities. The data for the variable costs a_{ij} , fixed cost b_k , and the capacity requirements d_{ijk} are given in the other document, i.e., Chhabra and Soland (1980).

For the test problem with $m=5$, $n=4$, and $p=8$, runs 4a, 4b, and 4c are the same except for 'no different intermediate steps' option

TABLE 4
ZIPCAP TFSR RESULTS

Problem Size							CODE USED									
						ZIP3OC		ZIPCAP								
m	n	p	Number of Vertices	Number of Edges	Number of Nodes	Capacitated/ Uncapacitated	Data Information	Run Number	Elapsed Time in Seconds	Elapsed Time in Seconds	Number of Nodes					
3	4	5	[17]	9	9	Capacitated		1	0.987	1	1	0	0.0	0.017	3	
						$s_k = 400, 400,$ $1000, 400, 400$	As given in the other document									
						$s_k = 700 \text{ V}k$	-,-	2	0.679	1	1	0	0.0	0.035	9	
						$s_k = 3000 \text{ V}k$	-,-	3	1.144	1	1	0	0.0	0.018	3	
5	4	8	[28]	12	12	Capacitated		4a	2.421	1	1	0	0.0	0.082	9	
								4b		1	1	1	0	0.144	9	
								4c		1	1	2	0	0.0	2.033	9
								4d		1	0	0	0.0	0.124	19	
10	8	8	[38]	16	16	Uncapacitated		5	4.85.8	1	0	1	0.0	0.549	23	
							As given in the other document									
10	30	8	[308]	38	38	Uncapacitated		6a		1	0	1	0.002	55.0	8.229	125
								6b		1	0	0	0.0	55.0	19.397	277

(ISTEP) and this results in slight differences in the time taken to solve the problem. Runs 4a and 4d differ in that 4d does not use the capacity rule; the resulting difference in the total number of nodes explored to reach the optimal value points to the effectiveness of the capacity rule in conjunction with the bounding rule.

Run 5 shows the results for an uncapacitated problem with $m=10$, $n=8$, and $p=8$. Option ICAPR is not used since the capacity rule is not useful for an uncapacitated problem.

Another uncapacitated problem with $m=10$, $n=30$, and $p=8$ is solved in runs 6a and 6b. In run 6a, the epsilon value (EPS) is specified as 0.002. The solution value found by exploring 125 nodes may be suboptimal but is guaranteed to be within +0.2 percent of the optimal solution value. Run 6b is made with an epsilon value (EPS) of 0.0, and the optimal solution value is found in 277 nodes. A comparison of runs 6a and 6b shows that the number of nodes is less than half for a solution value that may be suboptimal but very close to the optimal solution value as compared to the number of nodes for an optimal solution value.

In general, a small difference between a solution value that may be suboptimal and the optimal solution value, translates into a significant difference in the corresponding number of nodes and the solution time required.

6. FURTHER CONSIDERATIONS

It was mentioned in Chapter 2 that it is possible to consider alternative formulations of problem (P), and also to consider choices of Lagrange multipliers other than $v_k = b_k$ with the purpose of obtaining "tighter" bounds which, in turn, would further improve the efficiency of the branch-and-bound procedure. These aspects will be discussed in this Chapter.

6.1 Alternative Formulations

Problem (P) can be reformulated by adding additional constraints such that the corresponding Lagrangian relaxation(s), if solved, would provide "tighter" bounds. If such a relaxation does not possess the integrality property, then it provides an equal or better bound compared to that from an LP relaxation, as mentioned in Chapter 2.

Two alternative formulations of problem (P), along with their Lagrangian relaxations, are given below.

6.1.1 Alternative Formulation 1

Formulation (AP1) is obtained by adding the constraints $e_{ik} x_{ij} \leq y_k$, for all i, j , and k , to problem (P), i.e.,

$$\left\{ \begin{array}{ll}
 \text{Minimize} & \sum_i \sum_j a_{ij} x_{ij} + \sum_k b_k y_k & (4) \\
 \text{subject to} & \sum_i x_{ij} = 1 & \forall j & (2) \\
 (AP1) & \sum_i \sum_j r_{ijk} x_{ij} \leq y_k & \forall k & (5') \\
 & e_{ik} x_{ij} \leq y_k & \forall i, j, k & (52) \\
 & x_{ij}, y_k = 0 \text{ or } 1 & \forall i, j, k & (6)
 \end{array} \right.$$

Since $e_{ik} = 1$ or 0, each constraint of (52) is either equivalent to $x_{ij} \leq y_k$ (if $e_{ik} = 1$) or else is redundant (if $e_{ik} = 0$). Problem (API) thus has, at most, mnp additional constraints relative to problem (P). Two Lagrangian relaxations are now considered for problem (AP1).

The first Lagrangian relaxation is obtained with respect to constraints (5') by introducing nonnegative Lagrange multipliers $v_k \geq 0$ to get

$$\text{Minimize } \sum_i \sum_j a_{ij} x_{ij} + \sum_k b_k y_k - \sum_k v_k \left(y_k - \sum_i \sum_j r_{ijk} x_{ij} \right)$$

subject to (2), (52), and (6), or equivalently,

$$\left\{ \begin{array}{ll} \text{Minimize} & \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k v_k r_{ijk} \right) - \sum_k y_k \left(v_k - b_k \right) & (53) \\ \text{subject to} & \sum_i x_{ij} = 1 & \forall j & (2) \\ & e_{ik} x_{ij} \leq y_k & \forall i, j, k & (52) \\ & x_{ij}, y_k = 0 \text{ or } 1 & \forall i, j, k & (6) \end{array} \right.$$

(ALR1_v)

Another Lagrangian relaxation of problem (AP1) is obtained with respect to constraints (5') and (52) by introducing nonnegative Lagrange multipliers v_k and λ_{ijk} , respectively, to get

$$\begin{aligned} \text{Minimize } & \sum_i \sum_j a_{ij} x_{ij} + \sum_k b_k y_k \\ & - \sum_k v_k \left(y_k - \sum_i \sum_j r_{ijk} x_{ij} \right) \\ & - \sum_i \sum_k \lambda_{ijk} \left(y_k - e_{ik} x_{ij} \right) \end{aligned}$$

subject to (2) and (6), or equivalently,

$$\left\{ \begin{array}{ll}
 \text{Minimize} & \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k v_k r_{ijk} + \sum_k e_{ik} \lambda_{ijk} \right) \\
 & - \sum_k y_k \left(v_k + \sum_i \sum_j \lambda_{ijk} - b_k \right) \\
 \text{Subject to} & \sum_i x_{ij} = 1 \quad \forall j \\
 & x_{ij}, y_k = 0 \text{ or } 1 \quad \forall i, j, k
 \end{array} \right. \quad \begin{array}{l} (54) \\ (2) \\ (6) \end{array}$$

For this problem, the solution is:

$$\begin{aligned}
 y_k &= 0 \quad \text{if } \left(v_k + \sum_i \sum_j \lambda_{ijk} - b_k \right) \leq 0, \\
 &= 1 \quad \text{if } \left(v_k + \sum_i \sum_j \lambda_{ijk} - b_k \right) \geq 0,
 \end{aligned}$$

and $x_{ij} = 1$ if i minimizes $\left(a_{\underline{i}j} + \sum_k v_k r_{\underline{i}jk} + \sum_k e_{\underline{i}k} \lambda_{\underline{i}jk} \right)$

over $\underline{\lambda}$.

We need good choices of Lagrange multipliers v_k with which to solve problem $(ALR1_v)$, and of Lagrange multipliers v_k and λ_{ijk} with which to solve problem $(ALR1_{v,\lambda})$. Problem $(ALR1_v)$ does not possess the integrality property, thus offering the hope of a tight bound, but has more constraints and is difficult to solve compared to problem $(ALR1_{v,\lambda})$ which, on the other hand, involves more Lagrange multipliers.

6.1.2 Alternative Formulation 2

Another formulation of problem (P) is similar to problem (AP1) except for a modification in constraints (5'), i.e.,

$$\left\{
 \begin{array}{ll}
 \text{Minimize} & \sum_i \sum_j a_{ij} x_{ij} + \sum_k b_k y_k & (4) \\
 \text{Subject to} & \sum_i x_{ij} = 1 & \forall j & (2) \\
 & \sum_i \sum_j r_{ijk} x_{ij} \leq 1 & \forall k & (55) \\
 & e_{ik} x_{ij} \leq y_k & \forall i, j, k & (52) \\
 & x_{ij}, y_k = 0 \text{ or } 1 & \forall i, j, k & (6)
 \end{array}
 \right.$$

A Lagrangian relaxation with respect to constraints (55) and (52) is obtained by introducing nonnegative Lagrange multipliers v_k and λ_{ijk} to get

$$\begin{aligned}
 \text{Minimize} \quad & \sum_i \sum_j a_{ij} x_{ij} + \sum_k b_k y_k \\
 & - \sum_k v_k \left(1 - \sum_i \sum_j r_{ijk} x_{ij} \right) \\
 & - \sum_i \sum_j \sum_k \lambda_{ijk} \left(y_k - e_{ik} x_{ij} \right)
 \end{aligned}$$

Subject to (2) and (6), or equivalently,

$$\left\{
 \begin{array}{ll}
 \text{Minimize} & \sum_i \sum_j x_{ij} \left(a_{ij} + \sum_k v_k r_{ijk} + \sum_k e_{ik} \lambda_{ijk} \right) \\
 & + \sum_k y_k \left(b_k - \sum_i \sum_j \lambda_{ijk} \right) - \sum_k v_k & (56) \\
 \text{Subject to} & \sum_i x_{ij} = 1 & \forall j & (2) \\
 & x_{ij}, y_k = 0 \text{ or } 1 & \forall i, j, k & (6)
 \end{array}
 \right.$$

For this problem, the solution is:

$$\begin{aligned}
 y_k = 0 & \text{ if } \sum_i \sum_j \lambda_{ijk} \leq b_k, \\
 & = 1 \text{ if } \sum_i \sum_j \lambda_{ijk} \geq b_k,
 \end{aligned}$$

and $x_{ij} = 1$ if i minimizes $(a_{\underline{j}} + \sum_k v_k r_{\underline{j}k} + \sum_k e_{\underline{k}} \lambda_{\underline{j}k})$ over \underline{k} .

Here again, we need good choices of the Lagrange multipliers v_k and λ_{ijk} with which to solve problem $(ALR2_{v,\lambda})$.

6.1.3 Choice of Lagrange Multipliers

Each of the relaxations $(ALR1_{v,\lambda})$ and $(ALR2_{v,\lambda})$ involves $p v_k$ Lagrange multipliers and $mnp \lambda_{ijk}$ multipliers. If we have good choices of these multipliers, the resulting solutions of the relaxed problems should provide "tighter" bounds (because of the additional constraints) than the bound from relaxation (LR_v) . Since relaxations $(ALR1_{v,\lambda})$ and $(ALR2_{v,\lambda})$ are similar to a great extent, only the relaxation $(ALR1_{v,\lambda})$ will be considered for further discussion.

By looking at expression (54) of the formulation $(ALR1_{v,\lambda})$, a meaningful choice of the Lagrange multipliers v_k and λ_{ijk} appears to follow from setting

$$v_k + \sum_i \sum_j \lambda_{ijk} = b_k \quad \forall k \quad (57)$$

so that each of the λ_{ijk} can be chosen as

$$\left. \begin{array}{l} \lambda_{ijk} = \frac{b_k - v_k}{n(\sum_i e_{ik})} \quad \text{if } e_{ik} = 1, \\ = 0 \quad \text{otherwise} \end{array} \right\} \quad (58)$$

The solution for problem $(ALR1_{v,\lambda})$ is then to select, from each column j , an x_{ij} variable which minimizes $(a_{\underline{j}} + \sum_k v_k r_{\underline{j}k} + \sum_k e_{\underline{k}} \lambda_{\underline{j}k})$ over \underline{k} .

Arbitrary values were considered for the v_k (e.g., v_k equal to $3/4 b_k$, $1/2 b_k$, $1/4 b_k$, and 0), the λ_{ijk} were then computed from

(58), and the test problem with three designs (m), four activities (n) and five facilities (p) was solved. Three cases with different capacities s_k (as specified in Chapter 5, Table 4) were tried for the solutions at the initial node. The results, however, were not conclusive in terms of providing a meaningful choice of the Lagrange multipliers v_k (and of the λ_{ijk}).

Since the relaxation $(ALR_1_{v,\lambda})$ possesses the integrality property, a choice of the multipliers as the optimal values of the dual variables of the corresponding linear programming problem would provide a solution as good as the LP solution (as stated in Chapter 2). We do not propose to solve linear programs as a part of our branch-and-bound methodology. However, we have made some LP runs, basically to see if the results provide insight leading to the choice of the Lagrange multipliers, and also to see if the resulting LP solutions are "close" to the integer solutions. These results are given below.

The LP formulation $(\overline{AP1})$ corresponding to problem (AP1) is:

$$\left. \begin{array}{ll} \text{Minimize} & \sum_i \sum_j a_{ij} x_{ij} + \sum_k b_k y_k \\ \text{Subject to} & \sum_i x_{ij} = 1 \quad \forall j \\ & \sum_i \sum_k r_{ijk} x_{ij} \leq y_k \quad \forall k \\ & e_{ik} x_{ij} \leq y_k \quad \forall i, j, k \\ & y_k \leq 1 \quad \forall k \\ & x_{ij}, y_k \geq 0 \quad \forall i, j, k \end{array} \right\} \quad \begin{array}{l} (4) \\ (2) \\ (5') \\ (52) \\ (15) \\ (16) \end{array}$$

$(\overline{AP1})$

The constraints $x_{ij} \leq 1$ are implicit in constraints (2).

Problem $(\overline{AP1})$ was solved for the test problem with $m=3$, $n=4$, and $p=5$ and three different cases for the capacities s_k (as specified in

Chapter 5, Table 4). Each case was solved using the IMSL (International Mathematical and Statistical Library) Code ZX3LP on an IBM 3031 at The George Washington University.

Note that the formulation (\bar{P}) has up to mnp more constraints than the LP formulation (\bar{P}) given in Chapter 2. For our test problem, this translates into solving a problem of 17 variables and 50 constraints corresponding to formulation (\bar{P}) as against 17 variables and 14 constraints corresponding to formulation (\bar{P}) .

Table 5 lists the solution values for each of the three cases with different capacities for the small problem with three designs, four activities and five facilities. The solutions to problems (\bar{P}) and (\bar{P}) , obtained from ZX3LP, show the optimal solution values, the optimal values of the variables x_{ij} and y_k , and the optimal values of the dual variables corresponding to the Lagrangian relaxations (LR_v) and $(ALR_{v,\lambda})$, i.e., v_k associated with the capacity constraints (j') and λ_{ijk} associated with the constraints (52). The table also shows $Z(P)$, and the Lagrangian solution value $Z(LR_v)$ obtained by setting $v_k = b_k$ for all k at the root node, i.e., $Z(LR_b)$.

As expected, the LP solutions for each of the three cases show $Z(\bar{P})$ to be considerably higher than $Z(\bar{P})$, and closer to $Z(P)$, thereby providing a tighter bound. As for the Lagrange multipliers v_k and λ_{ijk} , the following relationships are observed.

$$\sum_i \sum_j \lambda_{ijk} \leq b_k \quad \forall k, \text{ and}$$

$$v_k + \sum_i \sum_j \lambda_{ijk} \geq b_k \quad \forall k.$$

Also, for $v_k = 0$, $\sum_i \sum_j \lambda_{ijk} = b_k$, and

$$\text{for } v_k \geq b_k, \sum_i \sum_j \lambda_{ijk} = 0 \quad \forall k.$$

TABLE 5
LP AND OTHER SOLUTION VALUES FOR A TEST PROBLEM
(m=3, n=4, AND p=5)

Test Problem Case	$Z(P)$	$Z(\bar{P})$	$Z(LP_0)$	$Z(\overline{LP_0})$
$\bullet_k = 700 V_k$	37,774.0	36,688.04	36,504.92	37,678.14
$x_{11}=1 \quad x_{22}=1 \quad x_{23}=1 \quad x_{24}=1$ $y_1=1 \quad y_2=1 \quad y_3=1 \quad y_4=1$	$x_{11}=0.2 \quad x_{32}=1 \quad x_{23}=1 \quad x_{24}=1$ $x_{21}=0.8$	$x_{11}=1 \quad x_{32}=1 \quad x_{23}=1 \quad x_{24}=1$	$x_{11}=0.05 \quad x_{22}=0.95 \quad x_{23}=0.95 \quad x_{24}=0.95$ $x_{21}=0.95 \quad x_{32}=0.05 \quad x_{33}=0.05 \quad x_{34}=0.05$	
$y_1=0.85 \quad y_2=0.05 \quad y_3=1$ $y_4=0.05 \quad y_5=0.85$	$v_1=1750 \quad v_2=2000 \quad v_3=2221$ $v_4=1350 \quad v_5=1000$	Solution Infeasible in problem (P)	$y_1=0.95 \quad y_2=0.05 \quad y_3=0.95 \quad y_4=0.05 \quad y_5=0.95$	
$v_1=0 \quad v_2=0 \quad v_3=1491.2 \quad v_4=0 \quad v_5=0$ $\lambda_{211}=377.2 \quad \lambda_{332}=1621.9 \quad \lambda_{233}=258.8 \quad \lambda_{324}=518.9 \quad \lambda_{277}=1000.0$ $\lambda_{231}=366.8 \quad \lambda_{342}=378.1 \quad \lambda_{344}=511.1$ $\lambda_{241}=16.6.0$				
$\bullet_k = 400, 400, 1000, 400, 400$	40,174.0	37,472.62	36,775.5	38,360.26
$x_{11}=1 \quad x_{22}=1 \quad x_{33}=1 \quad x_{24}=1$ $y_1=1 \quad y_2=1 \quad y_3=1 \quad y_4=1$ $y_5=1$	$x_{11}=1 \quad x_{22}=1 \quad x_{33}=0.8 \quad x_{44}=0.2$ $x_{21} \quad x_{31} \quad x_{33}=0.2 \quad x_{24}=0.8$	$x_{11}=1 \quad x_{32}=1 \quad x_{13}=1 \quad x_{24}=1$ $x_{21} \quad x_{31} \quad x_{33}=0.26 \quad x_{44}=0.55$	$x_{11}=1 \quad x_{22}=0.74 \quad x_{23}=0.74 \quad x_{14}=0.19$ $x_{32}=0.26 \quad x_{33}=0.26 \quad x_{44}=0.26$	
$y_1=1 \quad y_2=0.2 \quad y_3=1 \quad y_4=0.2$ $y_5=1$	$v_1=750 \quad v_2=2000 \quad v_3=5144$ $v_4=1350 \quad v_5=3879$	Solution Infeasible in problem (P)	$y_1=1 \quad y_2=0.26 \quad y_3=1 \quad y_4=0.26 \quad y_5=1$	
$v_1=4575.0 \quad v_2=0 \quad v_3=5063.0 \quad v_4=0 \quad v_5=270.0$ $\lambda_{322}=553.0 \quad \lambda_{324}=637.0$ $\lambda_{332}=1447.0 \quad \lambda_{344}=693.0$				
$\bullet_k = 3000 V_k$	37,429.0	33,156.2	33,156.2	36,756.0
$x_{11}=1 \quad x_{22}=1 \quad x_{23}=1 \quad x_{24}=1$ $y_1=1 \quad y_2=1 \quad y_3=1$	$x_{11}=1 \quad x_{32}=1 \quad x_{23}=1 \quad x_{24}=1$ $y_1=0.15 \quad y_2=0.01 \quad y_3=0.32$	$x_{11}=1 \quad x_{32}=1 \quad x_{23}=1 \quad x_{24}=1$ $y_4=0.01 \quad y_5=0.15$	$x_{11}=0.5 \quad x_{22}=0.5 \quad x_{13}=0.5 \quad x_{24}=0.5$ $x_{21}=0.5 \quad x_{32}=0.5 \quad x_{23}=0.5 \quad x_{34}=0.5$	
$v_1=1750 \quad v_2=2000 \quad v_3=1750$ $v_4=1350 \quad v_5=1000$		$y_1=0.5 \quad y_2=0.5 \quad y_3=0.5 \quad y_4=0.5 \quad y_5=0.5$		
$v_1=0 \quad v_2=0 \quad v_3=0 \quad v_4=0$ $\lambda_{221}=915.0 \quad \lambda_{322}=1412.0 \quad \lambda_{113}=1020.0 \quad \lambda_{324}=1350.0$ $\lambda_{231}=28.0 \quad \lambda_{362}=588.0 \quad \lambda_{213}=675.0$ $\lambda_{241}=807.0 \quad \lambda_{223}=55.0$				
$v_5=0$ $\lambda_{225}=1000.0$				

Although the relationship among various λ_{ijk} values is not apparent, the above observations are useful in further exploring some good choices of the Lagrange multipliers for the relaxation $(ALRL_{v,\lambda})$, as discussed earlier.

As for the "closeness" of the LP solution to that of the integer solution, most of the solution values x_{ij} and y_k of problem (\bar{P}) are fractional, and their rounding off to 0 or 1 does not, in general, seem to correspond to the optimal integer solution values x_{ij} and y_k of problem (P) .

Table 5 also displays $Z(LR_b)$ at the root node for each of the three cases. For $s_k = 3000$, $Z(LR_b) = Z(\bar{P})$, and the Lagrange multipliers, as reflected by the values of the dual variables of problem (\bar{P}) , are equal to b_k for all k . This is expected from Theorem 3 and our discussion of the integrality property in Chapter 2. Further, the dual variables of (\bar{P}) for the first two cases (i.e., $s_k = 700 \forall k$, and $s_k = 400, \dots$) have values $v_k \geq b_k$ from Theorem 1.

The $Z(LR_b)$ values in Table 5, however, take no consideration of the capacity rule and/or the facility usage rule of our branch-and-bound procedure. These rules, by fixing certain x_{ij} values to 0 or 1, and by forcing certain facilities into the solution, provide an improved lower bound. As per our branch-and-bound procedure the improved lower bound at the root node is obtained by solving problem (PR_1) . For example, for $s_k = 700 \forall k$, the values of $Z(LR_b)$ and $Z(PR_1)$ are shown in Figure 8. The figure also shows the values of $Z(\bar{P})$, $Z(\bar{A}P_1)$, and $Z(P)$. The branch-and-bound procedure rules provide an improved value of the lower bound $Z(PR_1)$ compared to $Z(\bar{P})$. It appears that some good values of the Lagrange multipliers of the relaxation $(ALRL_{v,\lambda})$, if found, could, in conjunction with these rules, provide significant improvement over $Z(\bar{A}P_1)$, and without the need to solve an LP problem.

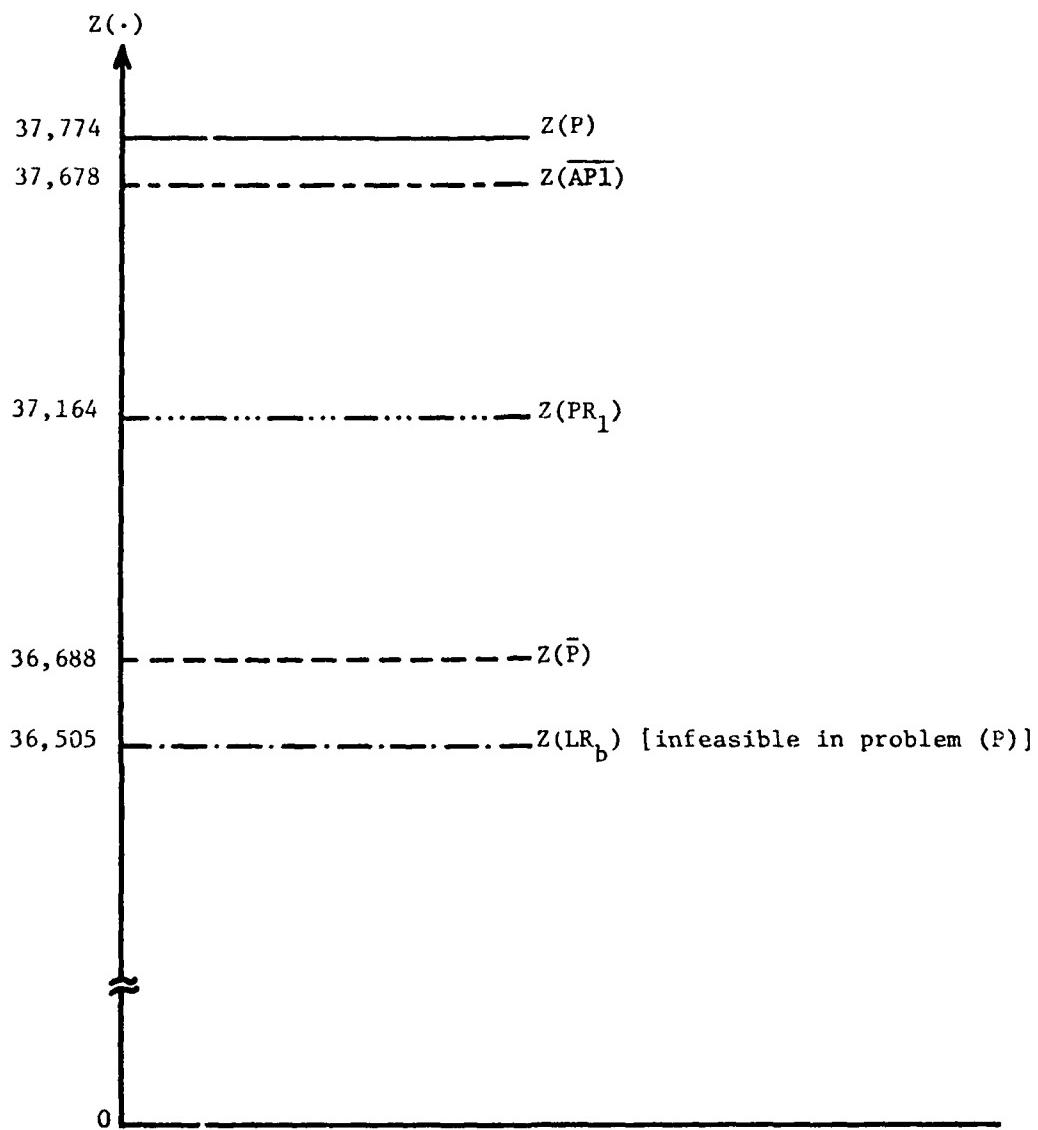


Figure 8

Lagrangian and other solution values for a test problem
(Test problem with m=3, n=4, p=5, and s_k = 700 V_k)

6.2 Subgradient Method

It was mentioned in Chapter 2 that setting the Lagrange multipliers v_k equal to b_k for all k provides a good starting point in solving the Lagrangian relaxation (LR_v^g) of problem (P). From Theorem 3, this choice is optimal (in terms of providing the tightest lower bound) if the resulting solution is feasible in problem (P). In other cases, i.e., where the resulting solution is not feasible in problem (P), this choice is generally not optimal and it is possible to tighten the bounds by considering values of $v_k \geq b_k$ (from Theorem 1). One method that seems useful in providing such a choice is the subgradient method.

The subgradient method is an adaptation of the gradient method in which gradients are replaced by subgradients. Through a heuristic choice of the step-size, this method has been successfully used to provide improved bounds and sometimes optimal solutions [for details see Held, Wolfe, and Crowder (1974), Fisher (1978), and Christofides (1980)]. The fundamental theoretical result is that

$$Z(LR_v^g) \rightarrow Z(D) \text{ if } t^g \rightarrow 0 \text{ and } \sum_{q=0}^g t^q \rightarrow \infty \text{ as } g \rightarrow \infty,$$

where t^g is the positive step-size t for the g th iteration, and $Z(LR_v^g)$ is the solution value of the relaxed problem (LR_v^g) using v_k values obtained at the g th iteration.

In the case of problem (P), the step-size t^{g+1} for iteration $g + 1$, given that we have a solution of (LR_v^g) , is given by

$$t^{g+1} = \frac{\lambda^{g+1} [z^* - Z(LR_v^g)]}{\sum_k |y_k^g - \sum_i \sum_j r_{ijk} x_{ij}^g|^2}, \quad (59)$$

where λ^{g+1} is a scalar and generally between 0 and 2, and z^* is an upper bound on $Z(LR_v^g)$, frequently obtained by applying a heuristic to solve problem (P).

Given the vector of multipliers v^g , v^{g+1} is generated by

$$v_k^{g+1} = v_k^g - t^{g+1} \left(y_k^g - \sum_{i,j} r_{ijk} x_{ij}^g \right), \quad (60)$$

where we enforce $v_k^{g+1} \geq b_k$ in our case of problem (P) (because of Theorem 1).

Justification for these rules and computational results of applications of the subgradient method are given in Held et al (1974). The scalar λ is generally initiated by setting $\lambda^1 = 2$ and halving subsequent λ 's whenever the resulting solution value has failed to increase in some fixed number of iterations. This rule has performed well empirically [Held et al (1974) and Fisher (1978)].

For the test problem with three designs, four activities, five facilities, and the capacities $s_1 = 400$, $s_2 = 400$, $s_3 = 1000$, $s_4 = 400$, $s_5 = 400$, the Lagrangian solution obtained at the root node by setting $v_k = b_k$ for all k , i.e., the solution to problem (PR₁) is infeasible in problem (P), i.e., it violates the capacity constraints. It seems that the subgradient method could be useful in considering $v_k \geq b_k$ with the ultimate purpose of obtaining a tighter lower bound, and, depending on the revised solution(s), possible improvement in the best upper bound. Another possibility could be to first arbitrarily increase the relevant v_k values by a small percentage of the b_k values and then solve problem (LR_v), hopefully to improve the lower bound; and thereafter to use the subgradient method for obtaining subsequent values of v_k , and tightening the bounds.

Both of the areas discussed above, i.e., the consideration of alternative formulations of problem (P), and the application of the subgradient method, and their combination, seem useful for continued research in terms of further improving the branch-and-bound procedure for solving the multiactivity multifacility capacity-constrained 0-1 assignment problems.

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APPENDIX A
ZIPCAP LISTING (REVISED)

FORTRAN IV G LEVEL 21 MAIN DATE = 80315 11/07/24

C ZIPCAP, A ZERO-ONE INTEGER PROGRAM IS DESIGNED 00000010
C TO SOLVE MULTIACTIVITY MULTIFACILITY CAPACITY- 00000015
C CONSTRAINED PROBLEMS HAVING VARIABLE AND FIXED 00000020
C COSTS. IT ALSO SOLVES UNCAPACITATED PROBLEMS AS A 00000030
C SPECIAL CASE 00000040
0001 INTEGER D(35,35,30), A(35,35), CX(35,35), E(35,30), 00000050
1 B(30), BSOLX(35), BSOLY(30), FL8(30), FIX(35), FIXI(35), 00000060
2 FUB(30), S(30), SOLX(35), STX(1225) 00000070
0002 REAL MINC(35), NMINC(35) 00000080
0003 DIMENSION C(35,35), DIFBR(35), KT2(35), MIND(35) 00000090
0004 INTEGER BRO, BRI, FC, FCUB, P 00000110
0005 REAL LOWB, MAXDIF, MINSC 00000120
C *****OPTIONS AVAILABLE: IINPT, ICAPR, ISTEP, IUNCAP, EPS 00000130
C IINPT=1 IF INPUT LISTING DESIRED; 0 OTHERWISE 00000140
C ICAPR=1 IF CAPACITY RULE TO BE USED; 0 OTHERWISE 00000150
C ISTEP=0 IF LISTING OF INTERMEDIATE STEPS 00000160
C NOT DESIRED. ISTEP=1 IF SUMMARY OF BRANCH & 00000170
C BOUND NODES DESIRED. ISTEP=2 IF DETAILED 00000180
C LISTING OF INTERMEDIATE STEPS DESIRED. 00000190
C IUNCAP=1 IF SOLVING AN UNCAPACITATED PROBLEM, 00000200
C 0 OTHERWISE. 00000210
C EPS= A FRACTIONAL VALUE IF SUBOPTIMAL 00000220
C SOLUTION DESIRED, E.G., EPSILON AS 0.005 00000230
C IMPLIES SOLUTION TO BE WITHIN ~0.5 PERCENT 00000240
C OF THE OPTIMAL SOLUTION. EPS=0.0 IF OPTIMAL 00000250
C SOLUTION DESIRED. 00000253
C ET= ELAPSED TIME IN SECONDS, IF SPECIFIED, AT 00000256
C WHICH THE NODE AND BOUNDS RELATED INFORMATION 00000260
C IS PRINTED. THIS IS USEFUL IN A SITUATION IF 00000263
C ISTEP=0 AND THE PROGRAM TERMINATES BEFORE 00000266
C REACHING THE FINAL SOLUTION. 00000270
C *****READ INPUT DATA***** 00000273
0006 READ 10, IINPT, ICAPR, ISTEP, IUNCAP, EPS, ET 00000280
0007 10 FORMAT (4I1, F6.5, F10.3) 00000290
C M= NUMBER OF DESIGNS 00000300
C N= NUMBER OF ACTIVITIES 00000310
C P= NUMBER OF FACILITIES 00000320
0008 READ 20,M,N,P 00000330
0009 20 FORMAT (3I5) 00000340
C A(I,J): VARIABLE COST MATRIX 00000350
0010 READ 30, ((A(I,J), I=1,M),J=1,N) 00000360
0011 30 FORMAT (8I10) 00000370
C B(K): FIXED COST VECTOR 00000380
0012 READ 30, (B(K),K=1,P) 00000390
0013 IF (IUNCAP.EQ.1) GO TO 40 00000400
C S(K): CAPACITY LIMIT VECTOR: REQUIRED ONLY 00000410
C IF IUNCAP=0 00000420
0014 READ 30, (S(K),K=1,P) 00000430
C D(I,J,K): CAPACITY USAGE MATRIX: REQUIRED 00000440
C ONLY IF IUNCAP=0 00000450
0015 DO 32 K=1,P 00000460
0016 READ 30, ((D(I,J,K), I=1,M),J=1,N) 00000470
0017 32 CONTINUE 00000480
0018 DO 37 K=1,P 00000490
0019 DO 37 I=1,M 00000500
0020 IF (D(I,I,K).EQ.0) GO TO 35 00000510
0021 E(I,K)=1 00000520
0022 GO TO 37 00000530

AD-A102 583 GEORGE WASHINGTON UNIV WASHINGTON DC PROGRAM IN LOGISTICS F/6 12/1
SOLVING MULTIACTIVITY MULTIFACILITY CAPACITY-CONSTRAINED 0-1 AS--ETC(U)
MAY 81 K L CHHABRA N00014-80-C-0169
UNCLASSIFIED SERIAL-T-441 NL

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FORTRAN IV G LEVEL 21	MAIN	DATE = 80315	11/07/24
0023	35 E(I,K)=0	00000540	
0024	37 CONTINUE	00000550	
0025	GO TO 90	00000560	
C	E(I,K): DESIGN=FACTORY MATRIX; REQUIRED ONLY	00000570	
C	IF IUNCAP=1	00000580	
C	40 READ 45,((E(I,K)),I=1,M),K=1,P)	00000590	
0027	45 FORMAT (80I1)	00000600	
0028	DO 80 K=1,P	00000610	
0029	S(K)=N	00000620	
0030	DO 75 I=1,M	00000630	
0031	IF (E(I,K).EQ.1) GO TO 65	00000640	
0032	DO 60 J=1,N	00000650	
0033	D(I,J,K)=0	00000660	
0034	60 CONTINUE	00000670	
0035	GO TO 75	00000680	
0036	65 DO 70 J=1,N	00000690	
0037	D(I,J,K)=1	00000700	
0038	70 CONTINUE	00000710	
0039	75 CONTINUE	00000720	
0040	80 CONTINUE	00000730	
C	*****PRINT INPUT DATA*****	00000740	
0041	90 PRINT 95, IINPT, ICAPR, ISTEP, IUNCAP, EPS, ET	00000750	
0042	95 FORMAT ('1',' OPTIONS SELECTED : IINPT=',I1,	00000760	
1	' ICAPR=',I1, ' ISTEP=',I1, ' IUNCAP=',I1,	00000770	
2	' EPS=',F8.5, ' ET=', F10.3///)	00000780	
0043	IF (IINPT.EQ.0) GO TO 168	00000790	
0044	PRINT 100,M,N,P	00000800	
0045	100 FORMAT ('0', T55, 'INPUT DATA',/1X, T55, '-----',//1X,	00000810	
	1T41, 'NUMBER OF DESIGNS (M)=', 4X,14//1X,T41,	00000820	
	2'NUMBER OF ACTIVITIES (N)=', 1X,14//1X, T41,	00000830	
	3'NUMBER OF FACILITIES (P)=',1X, I4///)	00000840	
0046	PRINT 105	00000850	
0047	105 FORMAT (4X, 'VARIABLE COST MATRIX A(I,J)',/4X,	00000860	
1'	'-----',/)	00000870	
0048	DO 110 I=1,M	00000880	
0049	110 PRINT 115, I, (A(I,J),J=1,N)	00000890	
0050	115 FORMAT ('0', T6, 'I=', I3, 4X,8I13, 4(/, 14X,8I13))	00000900	
0051	PRINT 120	00000910	
0052	120 FORMAT('0',//4X,'FIXED COST VECTOR B(K)',/4X,	00000920	
1'	'-----', /)	00000930	
0053	PRINT 122, (B(K),K=1,P)	00000940	
0054	122 FORMAT ('0', T15, 8I13, 3(/, 14X,8I13))	00000950	
0055	PRINT 125	00000960	
0056	125 FORMAT('0',//4X,'CAPACITY LIMIT VECTOR S(K)',/4X,	00000970	
1'	'-----', /)	00000980	
0057	PRINT 128, (S(K),K=1,P)	00000990	
0058	128 FORMAT ('0', T15, 8I13, 3(/, 14X,8I13))	00001000	
0059	PRINT 130	00001010	
0060	130 FORMAT('0',//4X, 'CAPACITY USAGE MATRIX D(I,J,K)',/4X,	00001020	
1'	'-----',/)	00001030	
0061	DO 150 K=1,P	00001040	
0062	PRINT 135,K	00001050	
0063	135 FORMAT ('0',//5X,'K=',I3/)	00001060	
0064	DO 145 I=1,M	00001070	
0065	PRINT 140,I,(D(I,J,K), J=1,N)	00001080	
0066	140 FORMAT ('0', T6, 'I=', I3, 4X,8I13, 4(/, 14X,8I13))	00001090	
0067	145 CONTINUE	00001100	
0068	150 CONTINUE	00001110	

FORTRAN IV G LEVEL 21	MAIN	DATE = R0315	11/07/24
0069	PRINT 155		00001120
0070	155 FORMAT('0',//4X,'DESIGN-FACILITY MATRIX E(I,K)',/4X, 1'-----',/)		00001130
0071	DO 160 I=1,M		00001140
0072	PRINT 158, I, (E(I,K),K=1,P)		00001160
0073	158 F0RMAT ('0', T6, 'I=', I3, 4X,8I13, 3(/, 14X,8I13))		00001170
0074	160 CON.IINUE		00001180
0075	162 IF (ISTEP.EQ.0) GO TO 190		00001190
0076	IF (ISTEP.EQ.1) GO TO 175		00001200
0077	PRINT 170		00001210
0078	170 FORMAT ('0',//55X,'DETAILED LISTING OF STEPS',/)		00001220
0079	GO TO 190		00001230
0080	175 PRINT 180		00001240
0081	180 FORMAT ('0',//55X,'SUMMARY OF STEPS',/)		00001250
C	*****INITIALIZE*****		00001260
0082	190 BUB=999999.		00001270
0083	BUBS= BUB/ (1.0+EPS)		00001280
0084	NSX=0		00001290
0085	NOD=1		00001310
0086	I8NOD=1		00001315
0087	INET=0		00001320
0088	INSET=0		00001330
0089	DO 205 J=1,N		00001390
0090	F:X(J)=0		00001400
0091	KT2(J)=0		00001410
0092	DO 205 I=1,M		00001420
0093	CX(I,J)=0		00001430
0094	205 CONTINUE		00001433
0095	LQ1=0		00001436
0096	LQ2=0		00001440
0097	LR2=0		00001443
0098	CALL TIMET(IT0)		00001445
0099	IF (ISTEP.EQ.0) GO TO 208		00001448
0100	PRINT 220,NOD		00001450
0101	208 IF(NSX.EQ.0) GO TO 283		00001453
C	CX(I,J) CONTAINS FIXED AND FREE X(I,J) VARIABLES.		00001456
C	STX(INS) CONTAINS FIXED X(I,J) VARIABLES.		00001460
C	CX(I,J) AND STX(INS) ARE UPDATED BY THE CAPACITY		00001480
C	RULE, THE BOUNDING RULE, AND THE RULE FOR		00001490
C	BRANCHING AND BACKTRACKING.		00001500
C	IN CX(I,J) A FIXED VARIABLE IS RECORDED AS 1 OR		00001505
C	2, AND A FREE VARIABLE AS 0.		00001510
C	A VALUE OF 1 IMPLIES THAT THAT PARTICULAR VARIABLE		00001515
C	IS FIXED, AND FIX(J) IS SET EQUAL TO 1 IMPLYING		00001520
C	THAT COLUMN J HAS A FIXED VARIABLE OF VALUE 1.		00001525
C	A VALUE OF 2 IMPLIES THAT THAT PARTICULAR VARIABLE		00001530
C	SHOULD NOT BE CONSIDERED FOR CURRENT COMPUTATIONS.		00001535
C	AN X(I,J) RECORDED IN CX(I,J) AS 1 DUE TO THE		00001540
C	BRANCHING RULE IS RECORDED IN STX(INS) AS X*100+J.		00001545
C	AN X(I,J) RECORDED IN CX(I,J) AS 1 DUE TO THE		00001550
C	CAPACITY RULE OR THE BOUNDING RULE IS RECORDED IN		00001555
C	STX(INS) AS (X*100+J)+100C000.		00001560
C	AN X(I,J) RECORDED IN CX(I,J) AS 2 IS RECORDED IN		00001565
C	STX(INS) AS -(X*100+J)-1000000.		00001570
0102	210 IF (ISTEP.EQ.0) GO TO 225		00001580
0103	215 PRINT 220,NOD		00001590
0104	220 FORMAT ('0',//6X,'NODE NUMBER', I7/)		00001600
C	*****UPDATE CX(I,J) FOR BRO*****		00001610

FORTRAN IV G LEVEL 21	MAIN	DATE = 80315	11/07/24
0105	C BRO IS THE RIGHT BRANCHING VARIABLE	00001615	
0106	225 LX=BRO	00001620	
0107	IX=LX/100	00001630	
0108	JX=LX-IX*100	00001640	
0109	CX(IX,JX)=2	00001650	
0110	KT2(JX)=KT2(JX)+1	00001660	
0111	FIX(JX)=0	00001720	
0112	LQ1=LQ1-1	00001725	
0113	IF (KT2(JX).LT.(M-1)) GO TO 270	00001730	
0114	DO 255 I=1,M	00001740	
0115	IF (CX(I,JX).EQ.2) GO TO 255	00001750	
0116	CX(I,JX)=1	00001760	
0117	NSX=NSX+1	00001763	
0118	STX(NSX)= (I*100+JX)+1000000	00001766	
0119	FIX(JX)=1	00001770	
0120	LQ1=LQ1+1	00001780	
0121	FIXI(JX)=1	00001790	
0122	GO TO 270	00001800	
0123	255 CONTINUE	00001810	
0124	270 LQ2=0	00001820	
0125	LR2=0	00001825	
0126	GO TO 283	00001830	
0127	272 IF (ISTEP.EQ.0) GO TO 276	00001840	
0128	PRINT 220,NOD	00001850	
0129	C *****UPDATE CX(I,J) FOR BR1*****	00001853	
0130	C BR1 IS THE LEFT BRANCHING VARIABLE	00001856	
0131	276 LQ2=0	00001860	
0132	LR2=0	00001866	
0133	LX=BR1	00001870	
0134	IX=LX/100	00001875	
0135	JX=LX-IX*100	00001880	
0136	CX(IX,JX)=1	00001885	
0137	FIX(JX)=1	00001890	
0138	LQ1=LQ1+1	00001892	
0139	DO 279 I=1,M	00001895	
0140	IF (IX.EQ.I) GO TO 281	00001897	
0141	279 CONTINUE	00001900	
0142	281 FIXI(JX)=IX	00001902	
0143	283 IF (ISTEP.NE.2) GO TO 303	00001905	
0144	285 DO 295 I=1,M	00001910	
0145	PRINT 290, I,(CX(I,J),J=1,N)	00001920	
0146	FORMAT (/5X,'CX(I,J)',4X,'I=',13,2X, 20I4/23X, 20I4)	00001930	
0147	295 CONTINUE	00001940	
0148	PRINT 297,(FIX(J),J=1,N)	00001950	
0149	297 FORMAT (/5X,'FIX(J)',12X, 20I4/23X, 20I4)	00001960	
0150	C *****APPLY CAPACITY RULE*****	00001970	
0151	C AND UPDATE CX(I,J) AND STX(INS).	00001980	
0152	303 DO 307 K=1,P	00002000	
0153	FLB(K)=0	00002015	
	307 CONTINUE	00002025	
	310 DO 2000 K=1,P	00002030	
	C FIND THE SUM OF MINIMUM D(I,J,K) OVER EACH J FOR A	00002040	
	C GIVEN K, I.E., MINSD= SUM OF *IND(J)	00002050	
	MINSD=0	00002060	
	DO 900 J=1,N	00002070	
	IF(FIX(J).EQ.0) GO TO 350	00002030	
	C IF FIX(J)=1, SET MIND(J)=D(I,J,K) FOR CX(I,J)=1	00002090	
	C AND MOVE TO NEXT COLUMN J	00002100	

FORTRAN IV G LEVEL 21	MAIN	DATE = 80315	11/07/24
0154	INDI=FIXI(J)		00002110
0155	MIND(J)=D(INDI,J,K)		00002120
0156	GO TO 800		00002130
0157	350 LK=0		00002160
0158	I=1		00002170
0159	MIND(J)=D(I,J,K)		00002180
	C SKIP D(I,J,K) WHEN CX(I,J)=2 & MOVE TO NEXT ROW I		00002190
0160	400 IF(CX(I,J).EQ.2) GO TO 600		00002200
0161	500 'F(D(I,J,K).LT.MIND(J)) MIND(J)=D(I,J,X)		00002210
0162	GO TO 700		00002220
0163	600 LK=LK+1		00002230
0164	IF(I.GT.LK) GO TO 700		00002240
0165	I=I+1		00002250
0166	MIND(J)=D(I,J,K)		00002260
0167	GO TO 750		00002270
0168	700 I=I+1		00002280
0169	750 IF(I.LE.M) GO TO 400		00002290
0170	800 MINSD=MINSD+MIND(J)		00002300
0171	900 CONTINUE		00002310
0172	910 IF (ISTEP.NE.2) GO TO 960		00002320
0173	PRINT 950, K, MINSD,(MIND(J),J=1,N)		00002330
0174	950 FORMAT ('0', 'K,MINSD,(MIND(J),J=1,N)', 10I10,4(/,44X,8I10))		00002340
0175	960 IF (MINSD.EQ.0) GO TO 975		00002342
0176	965 IF(FLB(K).EQ.1) GO TO 975		00002344
0177	970 F..B(K)=1		00002346
0178	975 IF (IUNCAP.EQ.1) GO TO 2000		00002348
0179	978 IF (ICAPR.EQ.0) GO TO 2000		00002349
	C FIND BALANCE AVAILABLE CAPACITY IBALD FOR A GIVEN K		00002350
	C IF IBALD IS NEGATIVE, THEN BACKTRACK.		00002360
0180	980 IBALD=S(K)-MINSD		00002380
0181	1000 IF (IBALD.LT.0) GO TO 6200		00002390
0182	DO 1500 J=1,N		00002400
	C SKIP COLUMN J IF FIX(J)=1		00002410
0183	IF (FIX(J).EQ.1) GO TO 1500		00002420
0184	DO 1300 I=1,M		00002430
	C SKIP ROW I IF CX(I,J)=2		00002440
0185	1100 IF(CX(I,J).EQ.2) GO TO 1300		00002450
	C COMPUTE DIFFERENCE BETWEEN D(I,J,K) AND MIND(J).		00002470
	C IF IT IS MORE THAN AVAILABE BALANCE, SET CX(I,J)=2		00002480
0186	1200 IDIFD=D(I,J,K)-MIND(J)		00002490
0187	IF ((IDIFD-JBALD).LE.0) GO TO 1300		00002510
0188	CX(I,J)=2		00002520
0189	NSX=NSX+1		00002523
0190	STX(NSX)=-(I*100+J)-1000000		00002526
	C LQ2 COUNTS THE NUMBER OF CX(I,J) VALUES SET EQUAL		00002530
	C TO 2 IN A CYCLE		00002540
0191	LQ2=LQ2+1		00002550
	C KT2(J) KEEPS AN ACCOUNT OF CX(I,J) VALUES SET EQUAL		00002560
	C TO 2 FOR COLUMN J		00002570
0192	KT2(J)=KT2(J)+1		00002580
	C FOR COLUMN J, IF ALL BUT ONE CX(I,J) VALUES ARE		00002590
	C EQUAL TO 2, SET THAT CX(I,J)=1 & SET FIX(J)=1		00002600
0193	IF(KT2(J).LT.(M-1)) GO TO 1300		00002610
0194	DO 1250 LR=1,M		00002620
0195	IF(CX(LR,J).EQ.2) GO TO 1250		00002630
0196	CA(' R,J)=1		00002640
0197	NSX=NSX+1		00002643
0198	STX(NSX)= (LR*100+J)+1000000		00002646

FORTRAN IV G LEVEL 21	MAIN	DATE = 80315	11/07/24
0199	FIX(J)=1		00002650
0200	C LQ1=LQ1+1	LQ1 KEEPS AN ACCOUNT OF COLUMNS FOR WHICH FIX(J)=1	00002655 00002660
0201	C FIXI(J)=LR	FIXI(J) SPECIFIES INDEX I FOR WHICH FIX(J)=1	00002662
0202	GO TO 1500		00002665
0203	1250 CONTINUE		00002680
0204	1300 CONTINUE		00002690
0205	1500 CONTINUE		00002700
0206	1800 IF (ISTEP.NE.2) GO TO 2000		00002710
0207	PRINT 1900, K, LQ2, LQ1		00002720
0208	1900 FORMAT ('0', 'K=', I3, ' LQ2=', I3, ' LQ1=', I3)		00002730
0209	DO 1930 I=1,M		00002740
0210	PRINT 290, I, (CX(I,J), J=1,N)		00002750
0211	1930 CONTINUE		00002770
0212	PRINT 297, (FIX(J), J=1,N)		00002780
0213	2000 CONTINUE		00002800
	C A CYCLE EXAMINES ALL THE FACILITIES.		00002803
	C IF IN A CYCLE, THE CAPACITY RULE RESULTS IN SETTING		00002810
	C ADDITIONAL CX(I,J) VALUES EQUAL TO 2, THEN REPEAT		00002820
	C THE CYCLE. BUT IF FIX(J)=1 FOR ALL J, THEN DO NOT		00002830
	C REPEAT THE CYCLE.		00002835
0214	IF (LQ1.EQ.N) GO TO 2400		00002840
0215	IF (LQ2.EQ.LR2) GO TO 2400		00002845
0216	2200 LR2=LQ2		00002860
0217	GO TO 310		00002870
	C *****SOLVE (LAGRANGIAN) RELAXED PROBLEM*****		00002880
	C UPDATE VECTOR OF FACILITIES FLB(K) FOR COMPUTING		00002890
	C (I,J) MATRIX & LOWER BOUND. IT HAS VALUE 1 IF A		00002900
	C FACILITY IS USED, OTHERWISE IT HAS 0 VALUE.		00002910
0218	2400 DO 3000 J=1,N		00002950
0219	IF (FIX(J).EQ.0) GO TO 3000		00002960
0220	INDI=FIXI(J)		00002970
0221	DO 2550 K=1,P		00002990
0222	IF (E(INDI,K).EQ.0) GO TO 2550		00003000
0223	IF (FLB(K).EQ.1) GO TO 2550		00003010
0224	FLB(K)=1		00003020
0225	2550 CONTINUE		00003030
0226	3000 CONTINUE		00003060
0227	IF (ISTEP.NE.2) GO TO 3150		00003070
0228	PRINT 3100, (FLB(K), K=1,P)		00003080
0229	3100 FORMAT ('0', '(FLB(K), K=1,P)', 20I4)		00003090
	C COMPUTE COST MATRIX C(I,J) FOR THE RELAXED PROBLEM		00003100
0230	3150 DO 3400 J=1,N		00003110
0231	DO 3300 I=1,M		00003120
0232	BSUM=0.0		00003130
0233	DO 3200 K=1,P		00003140
0234	IF (FLB(K).EQ.1) GO TO 3200		00003150
0235	IF (E(I,K).EQ.0) GO TO 3200		00003160
0236	BSUM=BSUM+(B(K) * (FLOAT(D(I,J,K))/ FLOAT(S(K)))))		00003170
0237	3200 CONTINUE		00003180
0238	3250 C(I,J)=A(I,J)+BSUM		00003190
0239	3300 CONTINUE		00003200
0240	3400 CONTINUE		00003210
0241	IF (ISTEP.NE.2) GO TO 3445		00003220
0242	DO 3430 I=1,M		00003230
0243	PRINT 3420, I, (C(I,J), J=1,N)		00003250
0244	3420 FORMAT 1/5X, 'C(I,J)', 5X, 'I=', I3, 2X, 5F15.4,		00003260

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	1	6(23X, 5F15.4)		00003265
0245	3430	CONTINUE		00003270
	C	FIND SUM OF MINIMUM C(I,J) VALUES OVER EACH J,		00003290
	C	I.E., MINSC=SUM OF MINC(J).		00003300
	C	IF FIX(J)=1, THEN MINC(J)=C(I,J) WHERE CX(I,J)=1		00003310
0246	3445	MINSC=0.0		00003320
0247		DO 3900 J=1,N		00003340
0248		IF (FIX(J).EQ.0) GO TO 3500		00003350
0249		INDI=FIXI(J)		00003360
0250		MINC(J)=C(INDI,J)		00003370
0251		SOLX(J)=INDI		00003380
0252		GO TO 3850		00003410
0253	3500	LK=0		00003430
0254		I=1		00003440
	C	SKIP C(I,J) ELEMENT IF CX(I,J)=2 & MOVE TO NEXT I		00003470
0255	3550	IF (CX(I,J).EQ.2) GO TO 3700		00003480
0256		IF ((I-LK).EQ.1) GO TO 3600		00003485
0257		IF (C(I,J).GE.MINC(J)) GO TO 3750		00003490
0258	3600	MINC(J)=C(I,J)		00003500
0259		IMIN=1		00003510
0260		GO TO 3750		00003520
0261	3700	LK=LK+1		00003530
0262	3750	I=I+1		00003590
0263	3800	IF (I.LE.M) GO TO 3550		00003600
0264		SOLX(J)=IMIN		00003610
0265		MINSC=MINSC+MINC(J)		00003620
0266	3900	CONTINUE		00003630
0267		IF (ISTEP.NE.2) GO TO 3940		00003640
0268		DO 3920 J=1,N		00003650
0269		PRINT 3910, J,MINC(J),SOLX(J)		00003660
0270	3910	FORMAT ('0', 'J,MINC(J),SOLX(J)', 15,F15.4,16)		00003670
0271	3920	CONTINUE		00003680
	C	COMPUTE FIXED COST FC FOR L(WER BOUND		00003710
0272	3940	FC=0		00003720
0273		DO 4000 K=1,P		00003730
0274		IF (FLB(K).EQ.0) GO TO 4000		00003740
0275	3950	FC=FC+B(K)		00003750
0276	/ 000	CONTINUE		00003760
	C	*****COMPUTE LOWER BOUND LOWB*****		00003770
0277	4050	LOWB=MINSC+FC		00003780
0278		IF (ISTEP.EQ.0) GO TO 4150		00003790
0279		PRINT 4120, MINSC, FC, LOWB		00003800
0280		4120 FORMAT ('0', ' MINSC, FC, LOWB ', F15.4, 115, F15.4)		00003810
	C	COMPARE LOWER BOUND WITH BEST UPPER BOUND STAR		00003820
	C	BUBS WHICH EQUALS BUB/(1+EPS). IF LOWB IS		00003830
	C	GREATER THAN OR EQUAL TO BUBS, THEN BACKTRACK		00003840
0281		4150 IF (LOWB.GE.BUBS)GO TO 6200		00003850
	C	CHECK IF CURRENT SOLUTION SATISFIES CAPACITY		00003880
	C	CONSTRAINTS		00003890
0282	4200	IF (IUNCAP.EQ.1) GO TO 4420		00003900
0283	4210	DO 4400 K=1,P		00003910
0284		NSUMD=0		00003920
0285		DO 4300 J=1,N		00003930
0286		IX=SGLX(J)		00003950
0287		NSUMD=NSUMD+D(IX,J, K)		00003960
0288	4300	CONTINUE		00003970
0289		IF (ISTEP.NE.2) GO TO 4320		00003980
0290		PRINT 4310, K,NSUMD		00003990

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0291 4310 FORMAT ('0', 'K,NSUMD',2I10) 00004000
0292 4320 IF(NSUMD.LE.S(K)) GO TO 4400 00004010
0293 GO TO 5100 00004020
0294 4400 CONTINUE 00004030
C *****COMPUTE UPPER BOUND UPB IF CAPACITY CONSTRAINTS 00004040
C ARE SATISFIED. 00004050
C UPB=SUM OF A(I,J)+FIXED COST FCUB BASED ON 00004060
C SOLUTION VECTOR SOLX(J) 00004070
C VECTOR OF FACILITIES FOR UPPER BOUND FUB(K) HAS 00004080
C VALUES 1 OR 0 BASED ON FACILITY USED OR OTHERWISE 00004090
0295 4420 DO 4450 K=1,P 00004100
FUB(K)=0
0296 4450 CONTINUE 00004110
0298 NSUMA=0 00004130
0299 FCUB=0 00004140
0300 4500 DO 4650 J=1,N 000 4150
IX=SOLX(J)
0301 NSUMA=NSUMA+A(IX,J) 00004170
0302 4550 DO 4600 K=1,P 00004180
0303 IF(E(IX,K).EQ.0) GO TO 4600 00004190
0304 IF(FUB(K).EQ.1) GO TO 4600 00004200
0305 FUB(K)=1 00004210
0306 FCUB=FCUB+B(K) 00004220
0307 4600 CONTINUE 00004230
0309 4650 CONTINUE 00004240
0310 IF (ISTEP.NE.2) GO TO 4700 00004250
0311 PRINT 4660, (FUB(K),K=1,P) 00004260
0312 4660 FORMAT('0',(FUB(K),K=1,P) ', 2014/16X,2014) 00004280
0313 UPB=NSUMA+FCUB 00004290
0314 4708 IF (ISTEP.EQ.0) GO TO 4750 00004300
0315 PRINT 4710, NSUMA, FCUB, UPB, BUB, BUBS 00004310
0316 4710 FORMAT('0',NSUMA, FCUB, UPB, BUB, BUBS ',2I10, .F15.4) 00004320
C COMPARE UPPER BOUND WITH BEST UPPER BOUND 00004330
C IF UPB IS LESS THAN BUB, SET IT AS BUB AND 00004340
C NOTE THE SOLUTION 00004350
0317 4750 IF (UPB.GE.BUB) GO TO 5100 00004360
0318 4770 BUB=UPB 00004370
0319 BUBS= BUB/ (1.0+EPS) 00004380
0320 IBNOD=NOD 00004385
0321 PRINT 4780, IBNOD, BUB, BUBS 00004386
0322 4780 FORMAT ('0', 'IBNOD, BUB, BUBS', I10, 2F15.4) 00004388
0323 DO 4800 J=1,N 00004390
0324 4800 BSOLX(J)=SOLX(J) 00004400
0325 DO 4850 K=1,P 00004410
0326 4850 BSOLY(K)=FUB(K) 00004420
C *****COMPARE LOWB WITH BUBS. IF LOWB IS GREATER 00004430
C THAN OR EQUAL TO BUBS, THEN BACKTRACK 00004440
0327 4900 IF (LOWB.GE.BUBS)GO TO 6200 00004450
C *****IF FIX(J) VALUES ARE 1 FOR EACH J, THEN BACKTRACK 00004480
0328 5100 IF (LQ1.EQ.N) GO TO 6200 00004500
C *****APPLY THE BOUNDING RULE***** 00004510
C IF THE DIFFERENCE BETWEEN C(I,J) AND MINC(J) IS 00004515
C GREATER THAN THE DIFFERENCE BETWEEN BUBS AND 00004520
C LOWB, THEN CX(I,J)=2 00004525
C *****APPLY BRANCHING RULE AND FIND BR1, THE NEXT 00004530
C VARIABLE FOR LEFT BRANCHING. 00004540
C FIND NMINC(J), THE NEXT HIGHER VALUE THAN MINC(J) 00004550
C AND DIFBR1(J), THE DIFFERENCE BETWEEN THEM. 00004555

FORTRAN IV G LEVEL 21	MAIN	DATE = 80315	11/07/24
0329	DBOUND=BUBS=LOWB		00004568
0330	5200 DO 5250 J=1,N		00004570
0331	NMINC(J)=0.0		00004580
0332	DIFBR(J)=0.0		00004590
0333	5250 CONTINUE		00004600
0334	DO 5600 J=1,N		00004610
C	SKIP TO NEXT J IF FIX(J)=1		00004620
0335	IF (FIX(J).EQ.1) GO TO 5600		00004630
0336	LK=0		00004640
0337	J=1		00004650
C	SKIP C(I,J) IF CX(I,J)=2 & MOVE TO NEXT I		00004670
0338	5300 IF (CX(I,J).EQ.2) GO TO 5350		00004680
0339	IF (I.EQ.SOLX(J)) GO TO 5350		00004690
0340	IF ((C(I,J)-MINC(J)).GT.DBOUND) GO TO 5330		00004700
0341	IF ((J-LK).EQ.1) GO TO 5320		00004710
0342	IF (C(I,J).GE.NMINC(J)) GO TO 5400		00004720
0343	NMINC(J)=C(I,J)		00004730
0344	GO TO 5400		00004735
0345	5330 CX(I,J)=2		00004740
0346	NSX=NSX+1		00004742
0347	STX(NSX)=-(I*100+J)-1000000		00004745
0348	KT2(J)=KT2(J)+1		00004747
0349	IF(KT2(J).LT.(M-1)) GO TO 5350		00004750
0350	INDI=SOLX(J)		00004752
0351	CX(INDI,J)=1		00004755
0352	NSX=NSX+1		00004758
0353	STX(NSX)= (INDI*100+J)+1000000		00004760
0354	FIX(J)=1		00004762
0355	LQ1=LQ1+1		00004764
0356	FIXI(J)=INDI		00004766
0357	GO TO 5600		00004768
0358	LK=LK+1		00004770
0359	I=I+1		00004775
0360	IF(I.LE.M) GO TO 5300		00004780
0361	5500 DIFBR(J)=NMINC(J)-MINC(J)		00004785
0362	5600 CONTINUE		00004795
0363	IF (ISTEP.NE.2) GO TO 5650		00004820
0364	DO 5620 I=1,M		00004830
0365	PRINT 290, I,(CX(I,J),J=1,N)		00004850
0366	5620 CONTINUE		00004860
0367	PRINT 297, (FIX(J),J=1,N)		00004880
C	IF FIX(J)=1 FOR ALL J, THEN BACKTRACK.		00004890
0368	5650 IF (LQ1.EQ.N) GO TO 6200		00004900
C	FIND MAXDIF, THE MAXIMUM DIFFERENCE DIFBR(J)		00004905
0369	LF=0		00004910
0370	DO 5800 J=1,N		00004915
0371	IF (FIX(J).EQ.1) GO TO 5690		00004920
0372	IF ((J-LF).EQ.1) GO TO 5660		00004925
0373	IF (DIFBR(J).LT.MAXDIF) GO TO 5800		00004930
0374	5660 MAXDIF=DIFBR(J)		00004935
0375	LJ=J		00004940
0376	GO TO 5800		00004943
0377	5690 LF=LF+1		00004946
0378	5800 CONTINUE		00004950
0379	IF !ISTEP.NE.2) GO TO 5840		00004953
0380	DO 5820 J=1,N		00004956
0381	IF (FIX(J).EQ.1) GO TO 5820		00004960
0382	PRINT 5810, J, NMINC(J), MINC(J), DIFBR(J)		

FORTRAN IV G LEVEL 21	MAIN	DATE = 90315	11/07/24
0383	5810 FORMAT ('0', 'J,NMINC(J),MINC(J),DIFBR(J)', 15,3F15.4)	00004963	
0384	5820 CONTINUE	00004966	
0385	C *****BRANCHING VARIABLE BRI CORRESPONDS TO MAXDIF*****	00004970	
0386	5840 DO 5900 J=1,N	00004980	
0387	IF (J.NE.LJ) GO TO 5900	00004990	
0388	5850 BRI=SOLX(J)*100+J	00005000	
0389	IF (ISTEP.EQ.0) GO TO 6020	00005010	
0390	PRINT 5880, BRI	00005020	
0391	5880 FORMAT('0', ' BRI', I10)	00005030	
0392	GO TO 6020	00005040	
0393	5900 CONTINUE	00005050	
0394	C *****UPDATE STX(INS) AND NSX*****	00005060	
0395	C NSX REPRESENTS THE NUMBER OF VARIABLES IN STX(INS)	00005070	
0396	6020 NSX=NSX+1	00005090	
0397	6040 STX(NSX)=BRI	00005100	
0398	IF (ISTEP.NE.2) GO TO 6100	00005150	
0399	PRINT 6088, (STX(INS), INS=1,NSX)	00005160	
0400	6088 FORMAT('0', ' STX(INS)', 10I10, 122(/, 10X,10I10))	00005170	
0401	C *****MOVE TO THE NEXT (LEFT BRANCH) NODE AND APPLY	00005220	
0402	C CAPACITY RULE	00005230	
0403	6100 NOD=NOD+1	00005240	
0404	6110 IF (ET.EQ.0.0) GO TO 6150	00005242	
0405	IF (INSET.EQ.1) GO TO 6147	00005244	
0406	IF (INET.EQ.1) GO TO 6150	00005246	
0407	CALL TIMET(INT)	00005248	
0408	ELTN=(INT-ITO)*26.04E-6	00005250	
0409	IF (ELTN.LT.ET) GO TO 6150	00005253	
0410	6120 PRINT 6125, NOD, ELTN, BUB, BUBS, IBNOD	00005256	
0411	6125 FORMAT ('0', 'WAS AT NODE', I6, ' AT ELAPSED TIME =', F10.4,	00005260	
0412	1 ' SECONDS.', /1X, ' BUB=', F15.4, ' BUBS=', F15.4,	00005263	
0413	2 ' AT NODE=', I7)	00005266	
0414	IBUB=BUB	00005267	
0415	IF (IBUB.EQ.9999999) GO TO 6146	00005268	
0416	6130 PRINT 6135, (BSOLX(J), J=1,N)	00005270	
0417	6135 FORMAT('0', 'SOLUTION CORRESPONDING TO BUB IS', //1X,	00005273	
0418	1 '(BSOLX(J), J=1,N)', 10I8, 3(/18X, 10I8))	00005276	
0419	6140 PRINT 6145, (BSOLY(K), K=1,P)	00005280	
0420	6145 FORMAT(/1X, '(BSOLY(K), K=1,P)', 10I8, 2(/18X, 10I8))	00005290	
0421	6146 INET=1	00005292	
0422	INIS=ISTEP	00005294	
0423	INSET=1	00005296	
0424	ISTEP=2	00005298	
0425	GO TO 6150	00005300	
0426	6147 ISTEP=INIS	00005302	
0427	INSET=0	00005304	
0428	6150 GO TO 272	00005306	
0429	C *****END IF AT THE ROOT NODE*****	00005308	
0430	6200 IF (NSX.EQ.0) GO TO 8100	00005310	
0431	6220 IF (IABS(STX(NSX)).GT.1000000) GO TO 6500	00005320	
0432	6250 BRO=STX(NSX)	00005330	
0433	6270 STX(NSX)=BRO-1000000	00005340	
0434	IF (ISTEP.EQ.0) GO TO 6308	00005390	
0435	PRINT 6305, BRO	00005400	
0436	6305 FORMAT('0', 'BRO ', I10)	00005410	
0437	6308 IF (ISTEP.NE.2) GO TO 6330	00005420	
0438	PRINT 6088, (STX(INS), INS=1,NSX)	00005430	
0439	C *****MOVE TO THE NEXT (RIGHT BRANCH) NODE AND APPLY	00005490	
0440	C CAPACITY RULE	00005500	

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0430	6330 NOD=NOD+1		00005510
0431	6410 IF (ET.EQ.0.0) GO TO 6450		00005512
0432	IF (INSET.EQ.1) GO TO 6445		00005516
0433	IF (INET.EC.1) GO TO 6450		00005518
0434	CALL TIMET(INT)		00005520
0435	ELTN=(INT-ITO)*26.04E-6		00005523
0436	IF (ELTN.LT.ET) GO TO 6450		00005526
0437	6420 PRINT 6125, NOD, ELTN, BUB, BUBS, IBNOD		00005528
0438	IBUB=BUB		00005530
0439	IF (IBUB.EQ.9999999) GO TO 6442		00005532
0440	6430 PRINT 6135, (BSOLX(J),J=1,N)		00005533
0441	6440 PRINT 6145, (BSOLY(K), K=1,P)		00005536
0442	INET=1		00005538
0443	INIS=ISTEP		00005540
0444	INSET=1		00005542
0445	ISTEP=2		00005544
0446	GO TO 6450		00005546
0447	6445 ISTEP=INIS		00005548
0448	INSET=0		00005550
0449	6450 GO TO 210		00005552
0450	6500 IF (STX(NSX).GT.1000000) GO TO 6520		00005555
0451	LX=STX(NSX)-1000000		00005560
0452	IX=LX/100		00005570
0453	JX=LX-IX*100		00005580
0454	CX(IX,JX)=0		00005590
0455	KT2(JX)=KT2(JX)-1		00005595
0456	GO TO 6550		00005600
0457	6520 LX= STX(NSX)-1000000		00005610
0458	IX=LX/100		00005620
0459	JX=LX-IX*100		00005630
0460	CX(IX,JX)=0		00005640
0461	FIX(JX)=0		00005650
0462	LQ1=LQ1-1		00005660
0463	6550 NSX=NSX-1		00005690
0464	GO TO 6200		00005700
	*****PRINT THE OUTPUT*****		
0465	8100 IBUB=BUB		00005730
0466	CALL TIMET(IT1)		00005740
0467	ELT1=(IT1-ITO)*26.04E-6		00005750
0468	PRINT 8105, ELT1		00005760
0469	8105 FORMAT ('0',//1X, 'ELAPSED TIME IN SECONDS=', F15.8)		00005770
0470	PRINT 8120, NOD		00005780
0471	8120 FORMAT ('0','TOTAL NUMBER OF NODES EXPLORED =',I3)		00005790
0472	IF (IBUB.EQ.9999999) GO TO 8350		00005800
0473	8130 PRINT 8150		00005810
0474	8150 FORMAT ('0', 'NOTE: 1. FOLLOWING X(I,J) VARIABLES SHOW DESIGN', 1 ' I TO WHICH ACTIVITY J IS ASSIGNED FOR J=1 TO N.', 2 '/7X, '2. IF EPSILON EPS WAS ASSIGNED A POSITIVE', 3 ' (NON-ZERO) VALUE, THE SOLUTION MAY BE SUBOPTIMAL.',/)		00005820
0475	8180 PRINT 8200, (BSOLX(J),J=1,N)		00005830
0476	8200 FORMAT('0',I55, 'OPTIMAL SOLUTION',//1X, TES, 1 '-----',//1X, 'X(I,J) WITH VALUE 1:',1018, 2 ' 3(/,21X,10I8))		00005840
0477	8220 PRINT 8250, (BSOLY(K), K=1,P)		00005850
0478	8250 FORMAT ('0', 'Y(K) VALUES:', 8X, 10I8, 2(/,21X,10I8))		00005860
0479	8280 PRINT 8300,IBUB		00005870
0480	8300 FORMAT ('0', 'OPTIMAL VALUE OF OBJECTIVE FUNCTION:', I15///)		00005880
0481	GO TO 8500		00005890

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0482	8350 PRINT 8400		00005960
0483	8400 FORMAT ('0', ' PROBLEM DOES NOT HAVE A FEASIBLE SOLUTION', 1 /IX, ' BECAUSE THE CAPACITY CONSTRAINTS CANNOT', 2 /IX, ' BE SATISFIED.',/)		00005970 00005980
0484	8500 PRINT 8550		00005990
0485	8550 FORMAT ('0', '*****NORMAL END OF JOB*****',/)		00006000
0486	6600 STOP		00006010
0487	END		00006020
			00006030

APPENDIX B

DETAILED PRINTOUT FOR A TEST PROBLEM
(TEST PROBLEM WITH $m=5$, $n=4$, AND $p=8$)

OPTIONS SELECTED : 1INP1=1 ICAPR=1 STEP=2 LNCAP=0 EPS= 0.0 ET= 0.0

INPUT DATA

NUMBER OF DESIGNS (M)= 5
NUMBER OF ACTIVITIES (N)= 4
NUMBER OF FACILITIES (P)= 6

VARIABLE COST MATRIX A(I,J)

I= 1	194951	218871	155094	104056
I= 2	235277	272087	143264	138641
I= 3	196138	220718	160399	107481
I= 4	198751	224042	167046	112465
I= 5	190873	229169	128361	112498

FIXED COST VECTOR B(K)

16000	16000	14000	25000	19000	31000
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CAPACITY LIMIT VECTOR S(K)

350	350	350	200	200	700	500	600
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CAPACITY USAGE MATRIX Q(I,J,K)

K= 1

I= 1	40	0	50	120
I= 2	80	40	100	160
K= 6				
I= 1	240	160	300	450
I= 2	0	0	0	0
I= 3	120	90	150	360
I= 4	0	0	0	0
I= 5	40	30	50	120

I= 1	160	160	200	360
I= 2	0	0	0	0
I= 3	80	60	100	240
I= 4	0	0	0	0
I= 5	160	160	200	360

I= 1	200	150	250	600
I= 2	40	30	50	180
I= 3	0	0	0	0
I= 4	0	0	0	0
I= 5	120	90	150	300

DESIGN-FACILITY MATRIX E11.K1

I= 1	1	1	1	1	1	1
I= 2	0	0	0	0	0	1
I= 3	1	1	1	1	1	0
I= 4	1	1	1	1	1	0

DETAILED LISTING OF STEPS

MODE NUMBER

1

CX(I,J)	I= 1	0	0	0	0
CX(I,J)	I= 2	0	0	0	0
CX(I,J)	I= 3	0	0	0	0
CX(I,J)	I= 4	0	0	0	0
CX(I,J)	I= 5	0	0	0	0
FIX(J)		0	0	0	0

Step 1

K=MIND,MIND(J,I),J=1,M1	1	0	0	0	0
K= 1 LQ2= 0 LQ1= 0					
CX(I,J)	I= 1	0	0	0	0
CX(I,J)	I= 2	0	0	0	0
CX(I,J)	I= 3	0	0	0	0
CX(I,J)	I= 4	0	0	0	0
CX(I,J)	I= 5	0	0	0	0
FIX(J)		0	0	0	0

Step 2 -- k=1

K=MIND,MIND(J,I),J=1,M1	2	0	0	0	0
K= 2 LQ2= 0 LQ1= 0					
CX(I,J)	I= 1	0	0	0	0
CX(I,J)	I= 2	0	0	0	0
CX(I,J)	I= 3	0	0	0	0
CX(I,J)	I= 4	0	0	0	0
CX(I,J)	I= 5	0	0	0	0
FIX(J)		0	0	0	0

Step 2 -- k=2

K=MIND,MIND(J,I),J=1,M1	3	0	0	0	0
K= 3 LQ2= 0 LQ1= 0					
CX(I,J)	I= 1	0	0	0	0
CX(I,J)	I= 2	0	0	0	0

Step 2 -- k=3

Step 2 -- k=4

```
LX(I,J)  I= 3   0   0   0   0  
CX(I,J)  I= 4   0   0   0   0  
CX(I,J)  I= 5   0   0   0   0  
  
FIX(I,J)  0   0   0   0   0  
  
K,MINSD,(MIND(I,J),J=1,N)  4   0   0   0   0   0  
K= 4  LQ2= 0  LQ1= 0  
CX(I,J)  I= 1   0   0   0   0  
CX(I,J)  I= 2   0   0   0   0  
CX(I,J)  I= 3   0   0   0   0  
CX(I,J)  I= 4   0   0   0   0  
CX(I,J)  I= 5   0   0   0   0  
  
FIX(I,J)  0   0   0   0   0
```

Step 2 -- k=5

```
K,MINSD,(MIND(I,J),J=1,N)  5   0   0   0   0   0
```

```
K= 5  LQ2= 0  LQ1= 0  
CX(I,J)  I= 1   0   0   0   0  
CX(I,J)  I= 2   0   0   0   0  
CX(I,J)  I= 3   0   0   0   0  
CX(I,J)  I= 4   0   0   0   0  
CX(I,J)  I= 5   0   0   0   0  
  
FIX(I,J)  0   0   0   0   0
```

Step 2 -- k=6

```
K,MINSD,(MIND(I,J),J=1,N)  6   0   0   0   0   0
```

```
K= 6  LQ2= 0  LQ1= 0  
CX(I,J)  I= 1   0   0   0   0  
CX(I,J)  I= 2   0   0   0   0  
CX(I,J)  I= 3   0   0   0   0  
CX(I,J)  I= 4   0   0   0   0  
CX(I,J)  I= 5   0   0   0   0  
  
FIX(I,J)  0   0   0   0   0
```

Step 2 -- k=7

```
K,MINSD,(MIND(I,J),J=1,N)  7   0   0   0   0   0
```

```
K= 7  LQ2= 0  LQ1= 0  
CX(I,J)  I= 1   0   0   0   0  
CX(I,J)  I= 2   0   0   0   0  
CX(I,J)  I= 3   0   0   0   0
```

Step 2 -- k=8

```

C(1,J)   I= 4   0   0   0   0
C(1,J)   I= 5   0   0   0   0
FIX(J)
      0   0   0   0
K,MIND,(MIND(J),J=1,N)   8   0   0   0   0   0   0
K= 0  LQ2= 0  LQ1= 0
C(1,J)   I= 1   0   0   0   0
C(1,J)   I= 2   0   0   0   0
C(1,J)   I= 3   0   0   0   0
C(1,J)   I= 4   0   0   0   0
C(1,J)   I= 5   0   0   0   0
FIX(J)
      0   0   0   0
(F,G(K),K=1,P)   0   0   0   0   0   0   0
C(1,J)   I= 1   239160.9375   262123.9375   210301.4375   205785.9375
C(1,J)   I= 2   236826.9375   273249.9375   145201.5000   145615.9375
C(1,J)   I= 3   224777.9375   249997.9375   196198.9375   177800.9375
C(1,J)   I= 4   209150.9375   231861.9375   180065.9375   143644.9375
C(1,J)   I= 5   214602.9375   253296.9375   157773.4375   167802.9375
J,MINC(J),SOLX(J)   1   209120.9375   4
J,MINC(J),SOLX(J)   2   231841.9375   4
J,MINC(J),SOLX(J)   3   145201.5000   2
J,MINC(J),SOLX(J)   4   143644.9375   4
P*NSC, FC, LDWB   720839.3125   0   729830.3125
K,NSUMD   1   190
K,NSUMD   2   190
K,NSUMD   3   190
K,NSUMD   4   190
K,NSUMU   5   190
K,NSUMU   6   0
K,NSUMD   7   0
K,NSUMD   8   50
(F,G(K),K=1,P)
NSUMA, FCUB, UPB, SUB, RUBS   676502   101000   779502.0000   9999999.0000   9999999.0000
10000. RUBS   1   779502.0000   779502.0000
Step 7

```

Step 11

CX(1,J)	I= 1	0	0	2	2
CX(1,J)	I= 2	0	0	0	0
CX(1,J)	I= 3	0	0	2	0
CX(1,J)	I= 4	0	0	0	0
CX(1,J)	I= 5	0	0	0	0
FIX(J)		0	0	0	0
J,MINC(J),MINC(J),DIFBR(J)	1	214402.9375	209150.9375	5252.0000	
J,MINC(J),MINC(J),DIFBR(J)	2	24997.9375	231441.9375	18156.0000	
J,MINC(J),MINC(J),DIFBR(J)	3	157773.4375	145201.5000	12571.9375	
J,MINC(J),MINC(J),DIFBR(J)	4	145615.9375	143644.9375	1971.0000	
BRI	402				
STX(INS)	-1000103	-1000303	-1000104	402	

NODE NUMBER

	2				
CX(1,J)	I= 1	0	0	2	2
CX(1,J)	I= 2	0	0	0	0
CX(1,J)	I= 3	0	0	2	0
CX(1,J)	I= 4	0	1	0	0
CX(1,J)	I= 5	0	0	0	0
FIX(J)		0	1	0	0
K,MIND(J),MIND(J,J=1,N)	1	30	0	30	0
K= 1 LQ2= 0 LQ1= 1					
CX(1,J)	I= 1	0	0	2	2
CX(1,J)	I= 2	0	0	0	0
CX(1,J)	I= 3	0	0	2	0
CX(1,J)	I= 4	0	1	0	0
CX(1,J)	I= 5	0	0	0	0
FIX(J)		0	1	0	0
K,MIND(J),MIND(J,J=1,N)	2	30	0	30	0
K= 2 LQ2= 0 LQ1= 1					
CX(1,J)	I= 1	0	0	2	2
CX(1,J)	I= 2	0	0	0	0

Step 2 -- k=1

K= 1 LQ2= 0 LQ1= 1					
CX(1,J)	I= 1	0	0	2	2
CX(1,J)	I= 2	0	0	0	0
CX(1,J)	I= 3	0	0	2	0
CX(1,J)	I= 4	0	1	0	0
CX(1,J)	I= 5	0	0	0	0
FIX(J)		0	1	0	0
K,MIND(J),MIND(J,J=1,N)	2	30	0	30	0
K= 2 LQ2= 0 LQ1= 1					
CX(1,J)	I= 1	0	0	2	2
CX(1,J)	I= 2	0	0	0	0

Step 2 -- k=2

CX(1,J) 1= 3 0 0 2 0
CX(1,J) 1= 4 0 1 0 0
CX(1,J) 1= 5 0 0 0 0
FIX(J)
K,MIND,I(MIND(J),J=1,M)
K= 3 LQ2= 0 LQ1= 1
CX(1,J) 1= 1 0 0 2 2
CX(1,J) 1= 2 0 0 0 0
CX(1,J) 1= 3 0 0 2 0
CX(1,J) 1= 4 0 1 0 0
CX(1,J) 1= 5 0 0 0 0
FIX(J)
K,MIND,I(MIND(J),J=1,M)
K= 4 LQ2= 2 LQ1= 1
CX(1,J) 1= 1 0 0 2 2
CX(1,J) 1= 2 0 0 0 0
CX(1,J) 1= 3 0 0 2 2
CX(1,J) 1= 4 0 1 0 0
CX(1,J) 1= 5 0 0 0 2
FIX(J)
K,MIND,I(MIND(J),J=1,M)
K= 5 LQ2= 7 LQ1= 1
CX(1,J) 1= 1 0 0 2 2
CX(1,J) 1= 2 0 0 0 0
CX(1,J) 1= 3 0 0 2 2
CX(1,J) 1= 4 0 1 0 0
CX(1,J) 1= 5 0 0 0 2
FIX(J)
K,MIND,I(MIND(J),J=1,M)
K= 6 LQ2= 2 LQ1= 1
CX(1,J) 1= 1 0 0 2 2
CX(1,J) 1= 2 0 0 0 0
CX(1,J) 1= 3 0 0 2 2
Step 2 -- k=3
Step 2 -- k=4
Step 2 -- k=5
Step 2 -- k=6

Step 2 -- k=7

CX(1,J)	I= 4	0 1 0 0
CX(1,J)	I= 5	0 0 0 2
FIX(J)		0 1 0 0
K,MINSD(MIND(J),J=1,N)		7 0 0 0 0 0 0 0
K= 7 LQ2= 2 LQ1= 1		
CX(1,J)	I= 1	0 0 2 2
CX(1,J)	I= 2	0 0 0 0
CX(1,J)	I= 3	0 0 2 2
CX(1,J)	I= 4	0 1 0 0
CX(1,J)	I= 5	0 0 0 2
FIX(J)		0 1 0 0

Step 2 -- k=8

K,MINSD(MIND(J),J=1,N)		8 0 0 0 0 0 0 0
K= 8 LQ2= 2 LQ1= 1		
CX(1,J)	I= 1	0 0 2 2
CX(1,J)	I= 2	0 0 0 0
CX(1,J)	I= 3	0 0 2 2
CX(1,J)	I= 4	0 1 0 0
CX(1,J)	I= 5	0 0 0 2
FIX(J)		0 1 0 0
K,MINSD(MIND(J),J=1,N)		1 30 0 0 30 0 0 0
K= 9 LQ2= 2 LQ1= 1		
CX(1,J)	I= 1	0 0 2 2
CX(1,J)	I= 2	0 0 0 0
CX(1,J)	I= 3	0 0 2 2
CX(1,J)	I= 4	0 1 0 0
CX(1,J)	I= 5	0 0 0 2
FIX(J)		0 1 0 0
K,MINSD(MIND(J),J=1,N)		2 30 0 0 30 0 0 0
K= 10 LQ2= 2 LQ1= 1		
CX(1,J)	I= 1	0 0 2 2
CX(1,J)	I= 2	0 0 0 0
CX(1,J)	I= 3	0 0 2 2
CX(1,J)	I= 4	0 1 0 0
CX(1,J)	I= 5	0 0 0 2
FIX(J)		0 1 0 0
Step 2 -- k=1 (Second Cycle)		
CX(1,J)	I= 1	0 0 2 2
CX(1,J)	I= 2	0 0 0 0
CX(1,J)	I= 3	0 0 2 2
CX(1,J)	I= 4	0 1 0 0
FIX(J)		0 1 0 0
Step 2 -- k=2 (Second Cycle)		
CX(1,J)	I= 1	0 0 2 2
CX(1,J)	I= 2	0 0 0 0
CX(1,J)	I= 3	0 0 2 2
CX(1,J)	I= 4	0 1 0 0

CX(I,J) I= 5 0 0 0 2
FIX(J) 0 1 0 0 0
K,MINSD,(MIND(J),J=1,N) 3 30 0 0 30 0 0 0
K= 3 LQ2= 2 LQ1= 1
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 0 0 0 0
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 0 1 3 0
CX(I,J) I= 5 0 0 0 2
FIX(J) 0 1 0 0 0
K,MINSD,(MIND(J),J=1,N) 4 30 0 0 30 0 0 0
K= 4 LQ2= 2 LQ1= 1
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 0 0 0 0
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 0 1 0 0
CX(I,J) I= 5 0 0 0 2
FIX(J) 0 1 0 0 0
K,MINSD,(MIND(J),J=1,N) 5 30 0 0 30 0 0 0
K= 5 LQ2= 2 LQ1= 1
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 0 0 0 0
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 0 1 0 0
CX(I,J) I= 5 0 0 0 2
FIX(J) 0 1 0 0 0
K,MINSD,(MIND(J),J=1,N) 6 0 0 0 0 0 0 0
K= 6 LQ2= 2 LQ1= 1
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 0 0 0 0
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 0 1 0 0
CX(I,J) I= 5 0 0 0 2

Step 2 - - k=3
(Second Cycle)
Step 2 - - k=4
(Second Cycle)
Step 2 - - k=5
(Second Cycle)

Step 2 - - k=6
(Second Cycle)

Step 2 - - k=7
(Second Cycle)

K,MINSC,MININD(J),J=1,M1	7	0	0	0	0	0	0
K= 7 LQ2= 2 LQ1= 1							
CX(1,J)	1= 1	0	0	2	2		
CX(1,J)	1= 2	0	0	0	0		
CX(1,J)	1= 3	0	0	2	2		
CX(1,J)	1= 4	0	1	0	0		
CX(1,J)	1= 5	0	0	0	2		
FIX(J)		0	1	0	0		
K,MINSD,MIND(J),J=1,M1	8	0	0	0	0	0	0
K= 8 LQ2= 2 LQ1= 1							
CX(1,J)	1= 1	0	0	2	2		
CX(1,J)	1= 2	0	0	0	0		
CX(1,J)	1= 3	0	0	2	2		
CX(1,J)	1= 4	0	1	0	0		
CX(1,J)	1= 5	0	0	0	2		
FIX(J)		0	1	0	0		
(FLB(K),K=1,P)	1	1	1	1	0	0	0
C(1,J)	1= 1	21830.9375	23823.4375	184381.4375	156985.9375		
C(1,J)	1= 2	236226.9375	273249.4375	145201.5000	145615.9375		
C(1,J)	1= 3	203977.9375	226597.9375	170198.9375	131000.9375		
C(1,J)	1= 4	198751.0000	224042.0000	167016.0000	112445.0000		
C(1,J)	1= 5	203202.9375	240696.4375	143773.4375	142602.9375		
J,MINC(J),SOLX(J)	1	198751.0000	4				
J,MINC(J),SOLX(J)	2	224042.0000	4				
J,MINC(J),SOLX(J)	3	143773.4375	5				
J,MINC(J),SOLX(J)	4	112445.0000	4				
MINSC, FC, LOW6	679011.4375	70000	749011.4375				
K,NSUMD	1	190					
K,NSUMD	2	190					
K,NSUMD	3	190					
K,NSUMD	4	200					
CX(1,J)	1= 1	0	0	2	2		

Step 2 - - k=8
(Second Cycle)

Step 3

Step 4

Step 6

Step 11

Step 11 (continued)

CX(1,J)	I= 2	2	0	0	2
CX(1,J)	I= 3	0	0	2	2
CX(1,J)	I= 4	0	1	0	1
CX(1,J)	I= 5	0	0	0	2
FIX(1,J)		0	1	0	1
J,MINC(1,J),MINC(1,J),DIFBR(J)	I	203202.9375	198751.0000	4451.9375	
J,MINC(1,J),MINC(1,J),DIFBR(J)	I	145201.5000	143773.4375	1428.0625	
BRI 1	401				
SIG(MNS) -1000103 -1000303 -1000104		402 -1000304 -1000504 -1000201 -1000204	1000404		

NODE NUMBER

3

R,MNSD,IMIND(J),J=1,N	I	190	40	30	0	120	
R= 1 LQ2= 0 LQ1= 3							Step 2 -- k=1
CX(1,J)	I= 1	0	0	2	2		
CX(1,J)	I= 2	2	0	0	2		
CX(1,J)	I= 3	0	0	2	2		
CX(1,J)	I= 4	1	1	0	1		
CX(1,J)	I= 5	0	0	0	2		
FIX(1,J)	I	1	0	1			
R,MNSD,IMIND(J),J=1,N	I	190	40	30	0	120	
R= 2 LQ2= 0 LQ1= 3							Step 2 -- k=2
CX(1,J)	I= 1	0	0	2	2		
CX(1,J)	I= 2	2	0	0	2		
CX(1,J)	I= 3	0	0	2	2		
CX(1,J)	I= 4	1	1	0	1		
CX(1,J)	I= 5	0	0	0	2		
FIX(1,J)	I	1	0	1			

Step 2 -- k=3

K,MINSD,IMIND(J),J=1,N) 1 1 0 1
K= 3 LQ2= 0 LQ1= 3
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 2 0 0 2
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 1 1 0 1
CX(I,J) I= 5 0 0 0 2
FIX(I) 1 1 0 1

Step 2 -- k=4

K,MINSD,IMIND(J),J=1,N) 4 190 40 30 0 120
K= 4 LQ2= 2 LQ1= 4
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 2 0 1 2
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 1 1 2 1
CX(I,J) I= 5 0 0 2 2
FIX(I) 1 1 1 1

Step 2 -- k=5

K,MINSD,IMIND(J),J=1,N) 5 190 40 30 0 120
K= 5 LQ2= 2 LQ1= 4
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 2 0 1 2
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 1 1 2 1
CX(I,J) I= 5 0 0 2 2
FIX(I) 1 1 1 1

Step 2 -- k=6

K,MINSD,IMIND(J),J=1,N) 6 0 0 0 0 0
K= 6 LQ2= 2 LQ1= 4
CX(I,J) I= 1 0 0 2 2
CX(I,J) I= 2 2 0 1 2
CX(I,J) I= 3 0 0 2 2
CX(I,J) I= 4 1 1 2 1
CX(I,J) I= 5 0 0 2 2
FIX(I) 1 1 1 1

K,MINSU,(MINC(J),J=1,M)	7	0	0	0	0	0	Step 2 -- k=7
K= 7 LQ2= 2 LC1= 4							
CX(1,J) I= 1 0 0 2 2							
CX(1,J) I= 2 2 0 1 2							
CX(1,J) I= 3 0 0 2 2							
CX(1,J) I= 4 1 1 2 1							
CX(1,J) I= 5 0 0 2 2							
FIX(J)	1 1 1 1						
K,MINSD,(MINSD(J),J=1,M)	6	50	0	0	50	0	Step 2 -- k=8
K= 8 LQ2= 2 LO1= 4							
CX(1,J) I= 1 0 0 2 2							
CX(1,J) I= 2 2 0 1 2							
CX(1,J) I= 3 0 0 2 2							
CX(1,J) I= 4 1 1 2 1							
CX(1,J) I= 5 0 0 2 2							
FIX(J)	1 1 1 1						
(FLBL(K),K=1,P)	1 1 1 1 0 0 1						Step 3
C(1,J) I= 1 210630.9375 232910.9375 174693.9375 135735.9375							
C(1,J) I= 2 235277.0000 272087.0000 143264.0000 138641.0000							
C(1,J) I= 3 203977.9375 225597.9375 170198.9375 131000.9375							
C(1,J) I= 4 198751.0000 211044.0000 167046.0000 112445.0000							
C(1,J) I= 5 128552.9375 237208.9375 137960.9375 130977.9375							
J,MINC(J),SOLX(J) I 1 198751.0000 4							
J,MINC(J),SOLX(J) I 2 224642.0000 4							
J,MINC(J),SOLX(J) I 3 143264.0000 2							
J,MINC(J),SOLX(J) I 4 112445.0000 4							
MIMSC, FC, LOMB 678502.0000 101000 779502.0000							
BAD 401							
STX(MMS) -1000103 -1000303 -1000104 402 -1000304 -1000504 -1000201 -1000204 1000404 -1000401							
MODE NUMBER	1 1 0 0 2 2						

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K,MINSU,(MIND(J),J=1,N) 1 150 0 30 0 120 Step 2 -- k=1
K= 1 LQ2= 0 LQ1= 2
CX(1,J) I= 2 2 0 0 2
CX(1,J) I= 3 0 0 2 2
CX(1,J) I= 4 2 1 0 1
CX(1,J) I= 5 0 0 0 2
FIX(J)
K,MINSU,(MIND(J),J=1,N) 1 150 0 30 0 120 Step 2 -- k=1
K= 2 LQ2= 0 LQ1= 2
CX(1,J) I= 1 0 0 2 2
CX(1,J) I= 2 2 0 0 2
CX(1,J) I= 3 0 0 2 2
CX(1,J) I= 4 2 1 0 1
CX(1,J) I= 5 0 0 0 2
FIX(J)
K,MINSU,(MIND(J),J=1,N) 2 150 0 30 0 120 Step 2 -- k=2
K= 3 LQ2= 0 LQ1= 2
CX(1,J) I= 1 0 0 2 2
CX(1,J) I= 2 2 0 0 2
CX(1,J) I= 3 0 0 2 2
CX(1,J) I= 4 2 1 0 1
CX(1,J) I= 5 0 0 0 2
FIX(J)
K,MINSU,(MIND(J),J=1,N) 3 150 0 30 0 120 Step 2 -- k=3
K= 4 LQ2= 0 LQ1= 2
CX(1,J) I= 1 0 0 2 2
CX(1,J) I= 2 2 0 0 2
CX(1,J) I= 3 0 0 2 2
CX(1,J) I= 4 2 1 0 1
CX(1,J) I= 5 0 0 0 2
FIX(J)
K,MINSU,(MIND(J),J=1,N) 4 230 00 30 0 120 Step 2 -- k=4
800 402
STR(NS) -1000103 -1000203 -1000104 -1000402 Step 12

(Last Page of Printout)

C(1,J)	I= 1	204550.9375	229670.9375	167093.9375	125655.9375
C(1,J)	I= 2	215277.0000	272087.0000	163264.0000	138661.0000
C(1,J)	I= 3	205737.9375	231517.9375	172398.9375	129080.9375
C(1,J)	I= 4	203550.9375	227641.9375	173055.9375	126844.9375
C(1,J)	I= 5	190873.0000	229169.0000	126361.0000	112496.0000
J,MINC(I,J),SOLX(J)	I 1	190873.0000	5		
J,MINR(I,J),SOLX(J)	I 2	229169.0000	5		
J,MINC(I,J),SOLX(J)	I 3	128361.0000	5		
J,MINC(I,J),SOLX(J)	I 4	138641.0000	2		
RINSC, FC, LOMB		687044.0000	106000	793044.0000	

ELAPSED TIME IN SECONDS = 2.03270542

TOTAL NUMBER OF NODES EXPLORER = 9

NOTE: 1. FOLLOWING X(I,J) VARIABLES SHOW DESIGN I TO WHICH ACTIVITY J IS ASSIGNED FOR J=1 TO N.
2. IF EPSILON EPS WAS ASSIGNED A POSITIVE (NON-ZERO) VALUE, THE SOLUTION MAY BE SUBOPTIMAL.

OPTIMAL SOLUTION

X(I,J) WITH VALUE 1:

VALUES:

OPTIMAL VALUE OF OBJECTIVE FUNCTION: 779502

*****END OF JOB*****

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